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MAPPING CANOPY COVER IN THE U.S. CARIBBEAN

USING 2016 & 2018 AIRBORNE LIDAR DATA

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ABSTRACT

Geospatial urban canopy cover data is increasingly recognized as a critical dataset for urban land managers, as urban tree cover provide a range of services. In many cases, however, urban canopy data is outdated or insufficiently precise to identify individual trees. Thankfully, lidar data, which is now one of the most common datasets used for urban canopy cover mapping, is becoming more widely available across the United States and its territories. The U.S. Department of Agriculture, Forest Service International Institute of Tropical Forestry and the Geospatial Technology and Applications Center partnered to produce tree canopy cover data across all of Puerto Rico and the U.S. Virgin Islands for 2016 (Puerto Rico only) and 2018. Using Esri's ArcGIS Pro, authors produced canopy height data and thresholded it to include only pixels above 2 meters, followed by the classification and removal of building footprints from the canopy data. The final data products produced include 1-meter binary canopy cover layers displaying the presence of canopy in 2016 and 2018, 1-meter canopy height models for 2016 and 2018, and building footprints for 2018.

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Photo by Preston Korns, USDA Forest Service

El Yunque National Forest, Puerto Rico's Northeast Region is the only tropical rainforest in the national forest system. At nearly 29,000 acres, it is one of the smallest in size, yet one of the most biologically diverse.

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Ecological systems include humid mountains and valleys of Puerto Rico, semiarid mountains and valleys of Puerto Rico and the U.S. Virgin Islands, humid coastal plains of Puerto Rico, and semiarid coastal plains of Puerto Rico and the U.S. Virgin Islands.

INTRODUCTION

Tree canopy cover is a commonly used metric in the U.S. Department of Agriculture, Forest Service. It provides data on tree distribution on the landscape and informs resource management activities such as forest thinning and habitat mapping. Canopy cover and the trees that create it are critical components of urban ecosystems, which provide important ecosystem services that range from reducing temperatures and energy costs to providing habitat for wildlife and improving human health ([Nyelele and Kroll, 2020](#)). Furthermore, canopy cover data is an important component of equity and environmental justice efforts, as studies have found that trees and the ecosystem services they provide are often unequally and inequitably distributed and/or managed in many cities ([McDonald et al., 2021](#); [Nyelele and Kroll, 2020](#)). These findings highlight the necessity of understanding the extent and distribution of canopy in

urban areas. One of the main challenges to managing and expanding urban tree canopy cover, however, is inventorying the location and extent of urban trees. High-resolution canopy cover maps are useful tools for identifying urban tree disparity and planning urban tree plantings and management in underserved communities to strategically increase ecosystem services.

Several tree canopy cover datasets are currently available for the U.S. Caribbean islands of Puerto Rico and the U.S. Virgin Islands, including the 2016 National Land Cover Database (NLCD) and the Coastal Change Analysis Program (C-CAP) land cover dataset. The 2016 NLCD is derived from medium-resolution (30-meter) Landsat data and includes a tree canopy cover component ([Dewitz et al., 2019](#); [Yang et al., 2018](#)). Although this tree canopy cover dataset is extremely useful for a variety of applications, it lacks a fine enough resolution to



Landslide damage after Hurricane Maria. Utuado, Puerto Rico, 2017. Almost 60% of trees lost branches, snapped in half, or were uprooted.

support analysis of tree canopy distributions in complex urban landscapes. It is common in these landscapes to have individual trees in backyards and surrounded by impermeable surfaces alongside streets. When aggregated, these smaller intraurban green spaces make up an important portion of permeable and vegetated land within a city, highlighting the importance of very high spatial resolution data for urban forestry and planning ([Ramos-González, 2014](#)).

C-CAP data, by contrast, is produced at a higher resolution (2-meter) and includes a forest class that provides a more detailed depiction of tree canopy cover in urban areas. However, C-CAP was last produced for Puerto Rico in 2010 and the U.S. Virgin Islands in 2012, meaning that there is a need for more recent high-resolution tree canopy cover data. The lack of regularly collected, high-resolution aerial imagery (e.g., the National Agriculture Imagery Program (NAIP)) means that there are few readily available resources to create canopy cover maps that can capture the fine-grained detail of urban systems. In 2017, Hurricanes Irma and Maria devastated Puerto Rico and the U.S. Virgin Islands,

furthering the need for up-to-date, high-resolution land cover and tree canopy cover maps that capture spatial information on infrastructure and vegetation across the islands. Although the U.S. Geological Survey (USGS) acquired lidar data over all of Puerto Rico in 2016–17, the data depicts prestorm conditions and does not capture any of the significant disturbances and loss of tree canopy cover caused by Hurricane Maria. To support disaster recovery efforts, the USGS helped fund another lidar acquisition in 2018–19 that captures posthurricane conditions in Puerto Rico and the U.S. Virgin Islands.

Recent urban canopy cover mapping efforts have demonstrated the effectiveness of using lidar data to map urban tree canopy cover at a fine scale over large cities in the United States ([O’Neil-Dunne et al., 2013](#); [MacFaden et al., 2012](#); [EarthDefine et al., 2018](#)). In addition, the strategic goals of the Forest Service Urban and Community Forestry Program highlight the need to continue developing strategies and protocols for mapping urban tree canopy cover data in Puerto Rico and the U.S. Virgin Islands. The Forest Service’s Geospatial Technology and Applications Center (GTAC) and the International



Photo by USDA Forest Service Geospatial Technology and Applications Center

Geospatial Technology and Application Center (GTAC) Set up GPS base stations for surveying a road damaged by landslides to support road repair work.

Institute of Tropical Forestry developed a workflow that produces high-resolution tree canopy cover data using available lidar data and Forest Service enterprise software. Once developed, remote sensing specialists at GTAC implemented this workflow across the 2016 and 2018 lidar data

acquisitions, resulting in 1-meter spatial resolution tree canopy cover data for 2016 and 2018. These data display the presence of tree canopy and were used to calculate percent canopy cover within administrative boundaries in Puerto Rico and the U.S. Virgin Islands.



BACKGROUND

PUERTO RICO AND THE U.S. VIRGIN ISLANDS

Puerto Rico and the U.S. Virgin Islands are two United States territories in the Caribbean Sea. Both territories are archipelagos comprised of many islands, islets, and cays. Puerto Rico has 1 main island (870,216 ha [2,150,351 acres]), the populated island municipalities of Vieques (13,321 ha [32,916 acres]) and Culebra (2,681 ha [6,625 acres]), and approximately 660 smaller isles and cays (Lugo et al., 2016). The U.S. Virgin Islands has 3 main islands: St. Thomas (7,125 ha [17,608 acres]), St. John (4,974 ha [12,291 acres]), and St. Croix (21,627 ha [53,442 acres]), and over 90 smaller islands and cays.

Although both territories are tropical islands that neighbor each other, they have distinct cultures,

geographies, and land use history. Puerto Rico's population of 3,263,584 is mostly Hispanic (98.7 percent) and claims both Spanish and English as official languages (U.S. Census Bureau, 2021). The U.S. Virgin Islands has a population of 87,146 with a 76-percent Afro-Caribbean majority, with English as its official language (U.S. Census Bureau, 2021).

Both island territories are in hurricane-prone areas. In 2017, Hurricanes Irma and Maria ([figure 1](#)) caused major disturbances in both U.S. Virgin Islands and Puerto Rico within a 2-week period. The combined trajectory of the category 5 and category 4 hurricanes affected the entirety of both territories. The hurricanes destroyed homes



Figure 1.—Tracks of hurricanes Fiona, Irma, and Maria near Puerto Rico and the U.S. Virgin Islands 2017–2022, ([Knapp et al., 2010](#); [Knapp et al. 2018](#)).



Paseo La Princesa, Old San Juan Puerto Rico. Photo by Maya Quinones, USDA Forest Service, IITF

Old San Juan Puerto Rico. Urban Tree Canopy (UTC) is the leafy, green, overhead cover from trees that community groups, residents, and local governments maintain in the landscape for a host of public health and educational values.

and infrastructure, left people without electric power for months (and some areas for up to a year), uprooted trees, defoliated forest canopy, deposited massive amounts of litterfall, caused widespread flooding, and triggered more than 40,000 landslides and mudslides ([Department of Natural and Environmental Resources, 2021](#); [Hilgemann and Morgan, 2021](#)). Forest inventories prior to 2014 performed by the Forest Service's Forest Inventory and Analysis (FIA) Program reported that forest land in the U.S. Virgin Islands has remained relatively stable since 2004 following a period of forest loss from 1994 to 2004 ([Marcano-Vega and Williamson, 2017](#)). The U.S. Virgin Islands has an estimated 57.2 percent of forest land. The most common tree species found in the islands

is the tan tan (*Leucaena leucocephala*), an introduced species.

In Puerto Rico, forest land reached an all-time low in the 1940s when it was estimated to account for 6 percent of the land ([Birdsey and Weaver, 1982](#)). Reforestation efforts and natural regeneration after socioeconomic changes in the island helped increase forest cover. In 1980 forest land was estimated at 31.3 percent, with a further increase to 52.8 percent in 2004 ([Marcano-Vega, 2017](#)). In the latest Forest Service FIA report ([Marcano-Vega, 2017](#)), Puerto Rico has an estimated 54.8 percent forest land, with the introduced African tulip tree (*Spathodea campanulata*) and native guaraguao (*Guarea guidonia*) comprising the most common tree species.

BENEFITS OF URBAN TREES

Urban tree canopy cover provides a range of ecosystem services that result in a variety of benefits to local communities. Nowak et al. (2007) discuss how New York City's urban forest plays a critical role in improving air quality, enhancing carbon storage and sequestration, and reducing energy use. Urban forests can improve air quality by removing pollutants from the air and providing shade during warmer months, which leads to a reduction in building energy use and helps mitigate the urban heat island effect (McDonald et al., 2021). Urban trees can also play an important role in sequestering carbon from the atmosphere, with larger, healthier trees sequestering more carbon. Moreover, significant urban canopy cover can reduce stormwater runoff and subsequent flooding (Dwyer et al., 1992), which

is particularly important in cities prone to significant rain events. Parks and green spaces offer recreational opportunities and attractive aesthetics for residents and are commonly associated with reduced stress and improved physical and mental health (Dwyer et al., 1992; USDA Forest Service, 2018). Quantifying the economic value of the services provided by urban forests is a field of study that has seen steady growth in the last several decades. McPherson et al. (2017), for instance, studied the economic value of ecosystem services provided by trees in urban California areas, estimating services such as energy conservation, carbon dioxide sequestration, stormwater retention, property values, and air purification combine for an annual value of \$8.3 billion.

NATIONAL TEN-YEAR URBAN AND COMMUNITY FORESTRY ACTION PLAN

In recognition of the environmental, economic, and social benefits of urban forests, the Forest Service collaborated with the National Urban and Community Forestry Advisory Council and other key stakeholders to develop the national “[Ten-Year Urban Forestry Action Plan: 2016-2026](#).” This plan lays out a series of goals and actions intended to improve the future status of urban forestry in the United States and its territories (NUCFAC, 2015). In addition to objectives focused on building a broader awareness of the importance of urban forests, the plan outlines a framework of research needs for the urban forestry community. Among these needs are the following objectives:

- Continue to develop strategies and protocols to measure and monitor extent and condition of urban forests and canopy cover.
- Continue original research to support development of additional assessment models and tools (such as [lidar] and hyperspectral remote sensing for forest canopy and health condition assessments, and iTree) (NUCFAC, 2015, p. 89)

These objectives highlight the need for geospatial data that capture the location and extent of urban canopy cover, as many urban areas lack these data.

In particular, the plan emphasizes the importance of continuing to develop remote sensing workflows that produce fine-scale urban canopy cover data-sets, as much of the existing data on tree canopy cover is out of date or relatively coarse (e.g., 30-meter spatial resolution) and not sufficiently detailed to inform urban tree inventories. These fine-scaled urban tree canopy cover maps are a vital data source that inform community forestry programs aimed at maintaining current canopy cover and informing community initiatives.



Photo by Dr. Tischa Muñoz USDA Forest Service, IITF

Guarda Rio community group members visiting the Río Piedras discuss nature base solutions and ecosystem services as part of the San Juan Urban Long-Term Research Area (ULTRA)

LIDAR TECHNOLOGY

As noted in the research objectives, one of the key data sources revolutionizing urban canopy cover maps is lidar. Lidar is an active remote sensing technology that captures 3D data representing the Earth's surface, vegetation, and other aboveground features. A unique aspect of lidar is that it can collect not only data at the top of the canopy but also subcanopy data that enables the mapping of the ground and vegetation structure in areas that would be obscured in most passive optical satellite or aerial imagery ([Lefsky et al., 2002](#)). This enables the production of high-resolution (1-meter) canopy height models (CHM; [figure 2](#)) and digital elevation models (DEM), as accurate canopy height measurements depend on accurate ground surface measurements. While the Forest Service [GTAC regularly works with lidar data](#), this project was one of the first at GTAC focused on mapping

canopy cover in urban environments. The following section introduces some existing canopy cover datasets derived from medium-resolution imagery, high-resolution imagery, lidar, or a combination of the latter two.

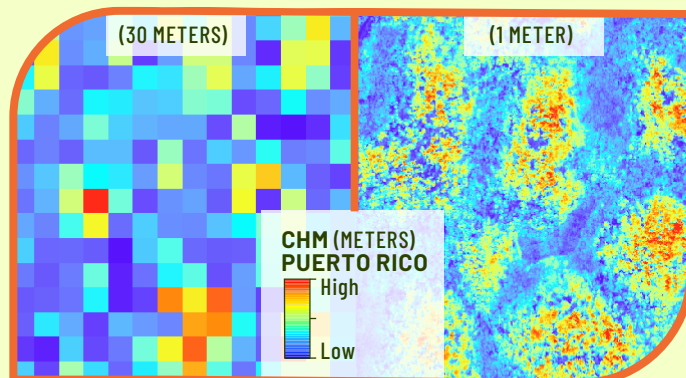


Figure 2.—Comparison of 30 meter and 1 meter canopy height models (CHM).

URBAN CANOPY COVER DATA

In Puerto Rico and the U.S. Virgin Islands, there are several available land cover datasets that either have a canopy cover class identifying the presence of tree canopy cover or have a standalone canopy cover layer displaying percent canopy cover. One of these is the National Land Cover Database

(NLCD), which is created from medium-resolution (30-meter) Landsat imagery and managed by the USGS ([Dewitz, 2019](#)). The NLCD provides a land cover dataset with a forest class as well as a stand-alone continuous canopy cover dataset ([figure 3](#)) displaying values from 0 to 100 percent. While this dataset

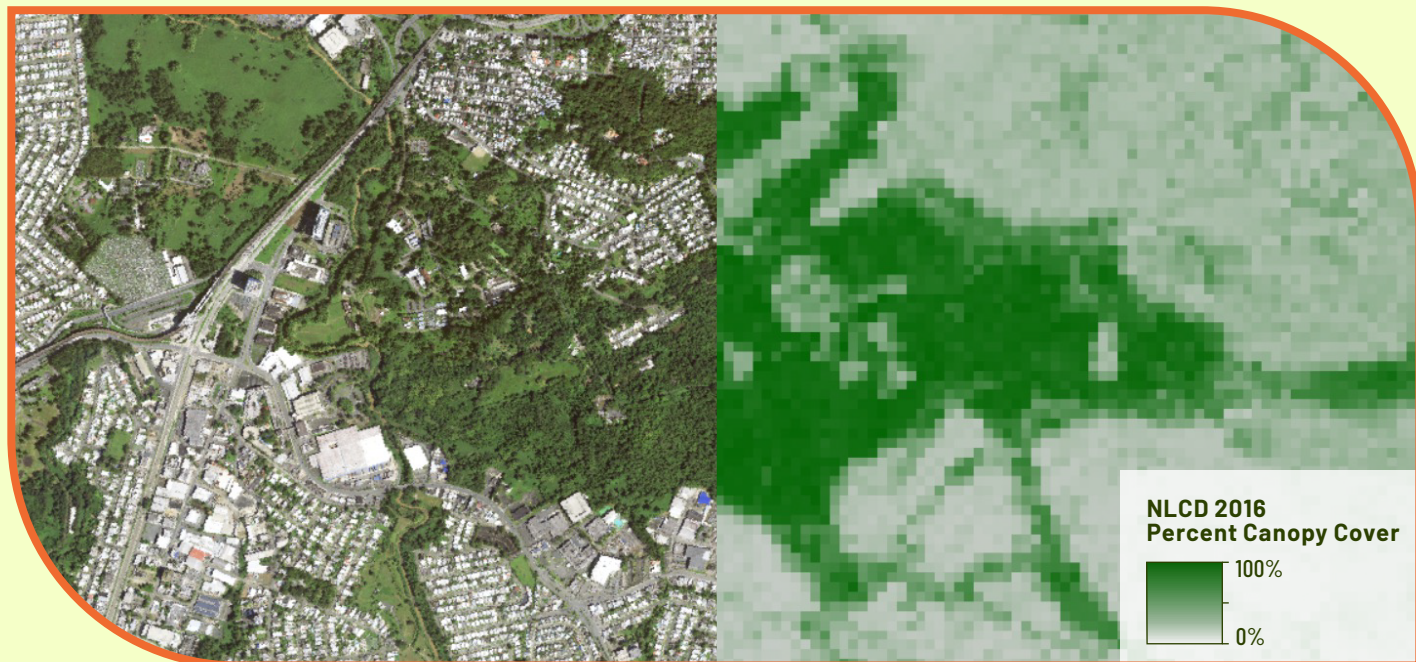


Figure 3.—High-resolution image (left) and National Land Cover Database (NLCD; right) of the same area, for part of the San Juan Ecological Corridor, Puerto Rico

depicts large, continuous forests very effectively and is useful for a variety of broad scale analyses, it lacks the spatial resolution required to visualize individual trees at the street level or the highly variable distribution of tree canopy within urban environments, which is essential for urban forestry management ([Moskal et al., 2011](#)).

Another land cover dataset available for both Puerto Rico and the U.S. Virgin Islands is the C-CAP land cover dataset, produced by the National Oceanic and Atmospheric Administration's (NOAA) Office for Coastal Management. As mentioned above, the Coastal Change Analysis Program (C-CAP) provides land cover data, which includes a forest class, at a 2-meter spatial resolution for Puerto Rico (2010) and the U.S. Virgin Islands (2012) ([Office for Coastal Management, 2022](#)). Initial land cover results were produced by combining object-based image analysis and a supervised classification approach using high-resolution (1-foot) aerial imagery, followed by thorough manual editing of classes. At a 2-meter spatial resolution, this C-CAP data offers a much finer resolution than the NLCD,

enabling a more precise assessment of urban canopy cover ([figure 4](#)). It also differs from the NLCD tree canopy cover layer in that it only displays the presence of canopy, not the percent cover. While C-CAP provides extremely useful urban tree canopy cover data, the most recent datasets produced for Puerto Rico and the U.S. Virgin Islands are over a decade old (and do not account for very large disturbance events, i.e., two destructive hurricanes), making them unsuitable for current urban canopy cover management activities.

In recent years, however, several projects have successfully produced high-resolution urban canopy cover datasets using combinations of high-resolution imagery and lidar data. MacFaden et al. (2012) demonstrated a complex approach that combines lidar data and high-resolution aerial imagery to map urban land cover in New York City, including buildings, roads, and tree canopy cover. They produced multiple 1-foot-resolution lidar raster products, including a canopy height model (CHM), lidar intensity, and a statistical raster depicting the standard deviation of elevation for



Figure 4.—High-resolution image of San Juan, Puerto Rico (left) compared with Coastal Change Analysis Program (C-CAP) land cover data (right) for the same area.

all lidar returns, which they used to help identify impervious surfaces. They coupled this with an object-based image analysis workflow and then performed manual editing on the final seven-class land cover map, with efforts primarily focused on omitted street trees and other objects incorrectly classified as trees. O’Neil-Dunne (2019) also used a combination of lidar data and 1-meter-resolution imagery from the National Agriculture Imagery Program (NAIP) to map urban canopy cover statewide for Delaware, Maryland, and Pennsylvania. This rules-based classification approach drew on spectral data from NAIP and height data from lidar to produce a canopy presence raster at a 1-meter resolution.

Other efforts have similarly demonstrated the effectiveness of using lidar data to produce fine-scale urban canopy cover maps. The Forest Service Pacific Southwest Region partnered with [EarthDefine LLC](#) and the California Department of Forestry and Fire Protection to map urban canopy cover in California ([EarthDefine LLC et al., 2018](#)) and Hawaii ([EarthDefine LLC et al., 2021](#)) using lidar and 60-centimeter-resolution imagery from the National Agricultural Imagery Program. The resulting products display

the location and extent of urban trees, with each State hosting an interactive map viewer ([California viewer](#); [Hawaii viewer](#)) where users can visualize the canopy cover product as well as view statistics on canopy cover summarized to census tracts ([figure 5](#)). Making these data easily accessible via such a web map is very valuable, as it enables a diverse range of stakeholders to visualize and assess the relationships between parcels, the built environment, and tree canopy, even without advanced geospatial analysis skills.

These successful urban canopy cover mapping efforts, the availability of lidar data for Puerto Rico and the U.S. Virgin Islands, and the current lack of high-quality urban canopy cover data for these locations were the impetuses for this project. The initial goal of this project was to pilot the use of available lidar data and Forest Service enterprise software to map canopy cover in urban areas across Puerto Rico. After successful completion of the pilot, the study authors expanded the project scope to include the full extents of two lidar acquisitions before and after Hurricanes Maria and Irma in September 2017.

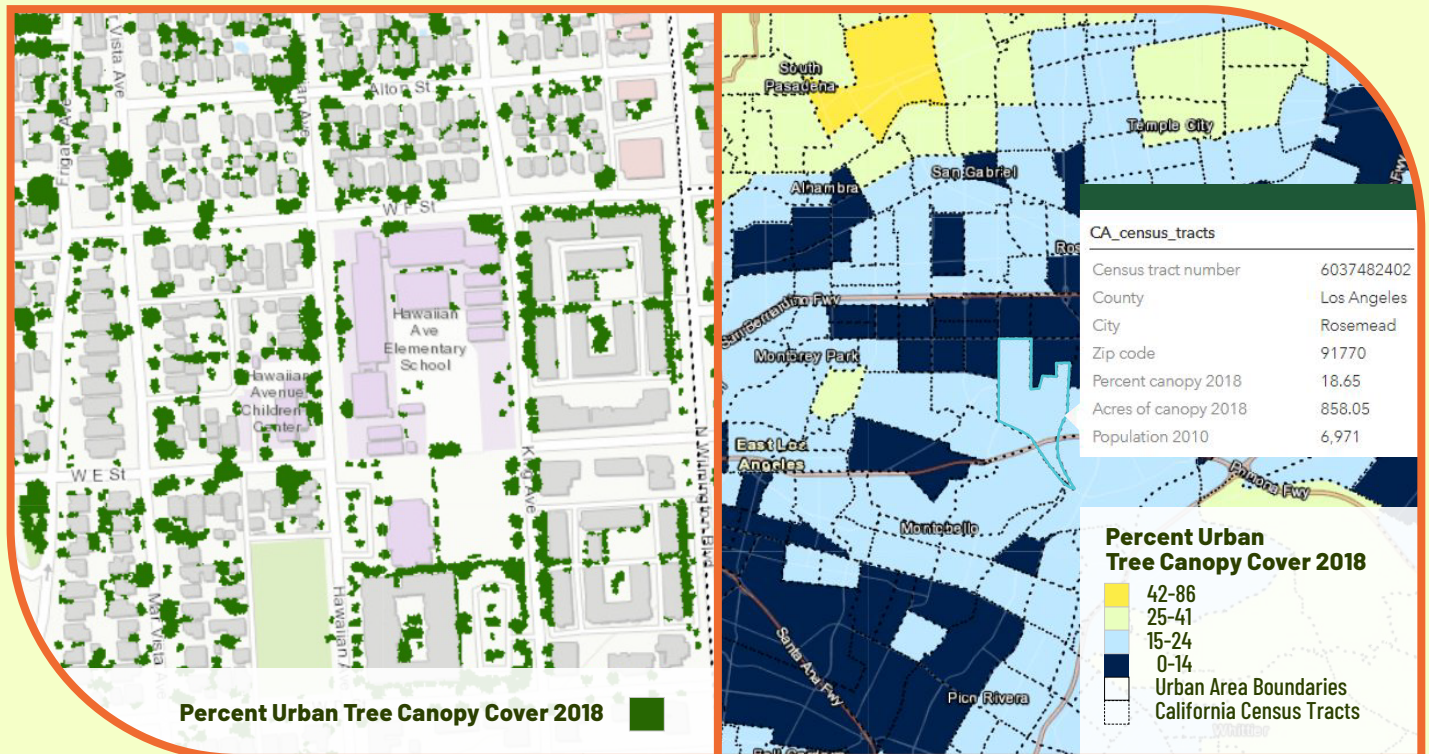


Figure 5.—Map of urban tree canopy in California. Canopy cover extent in green (left) and canopy cover and other statistics (right) displayed for a selected census tract.

METHODS

This section introduces the different datasets used in this project and describes the canopy cover mapping workflow from beginning to end. The goal of this workflow is to produce canopy

height data, threshold out values unlikely to be canopy, and then mask out building footprints from the canopy data to produce a final raster layer depicting canopy cover.

STUDY AREA AND LIDAR DATA

In 2016, lidar was acquired across all of Puerto Rico (3,451 square miles; acquisition does not include the U.S. Virgin Islands) at quality level 2, meaning the lidar pulse density was 2 pulses per m² or greater ([table 1](#)). The majority of the 2016 data was collected between January and May of 2016. However, due to persistent cloud cover and the inability to collect lidar in cloudy conditions, the southeastern portion of Puerto Rico was collected between December 2016 and March 2017, and part of the island was unable to be acquired at all and remains a data void ([figure 6](#)). To support disaster recovery efforts in the aftermath of Hurricanes Irma and Maria, a subsequent lidar acquisition was completed for all of Puerto Rico and the U.S. Virgin Islands (3,587 square miles). This quality level 1 acquisition (≥ 8 pulses per m²; [table 1](#)) was collected between August 2018 and April 2019, and like the 2016–2017 dataset there are data voids in the eastern and southeastern portions of Puerto Rico due to persistent cloud cover ([figure 6](#)).

Table 1.—Lidar quality level specifications, U.S. Geological Survey 3D Elevation Program Lidar Base Specification ([USGS, 2022](#)).

Quality Level (QL)	Nominal Pulse Spacing (m)	Nominal Pulse Density (pulses per m ²)
QL0	≤ 0.35	≥ 8.0
QL1	≤ 0.35	≥ 8.0
QL2	≤ 0.71	≥ 2.0
QL3	≤ 1.41	≥ 0.5

The authors used the vendor-delivered digital elevation model (DEM) (1-meter resolution) and point cloud datasets from each acquisition, which are disseminated by the USGS 3D Elevation Program. The point cloud datasets were delivered in LAZ file format (compressed LAS file format, which is a file type designed to store lidar point cloud data) with ground and noise points classified.

Figure 6.—Lidar acquisition extent and data voids from 2016 (light green) and 2018 (dark teal).



DATA MANAGEMENT

The workflow for this project was executed primarily in Esri ArcGIS Pro (versions 2.7.3 and 2.8.3). The DEMs for each acquisition are delivered in tiles; using the “Mosaic to New Raster” tool to create a single 1-meter DEM for the 2016 and 2018 acquisitions was the first step.

ArcGIS Pro requires point cloud data to be in LAS format (uncompressed) to create a LAS Dataset (.lasd), which is Esri’s file format for referencing LAS files and must be used to process data. Because the data consisted of lidar point cloud tiles that cover massive areas and totaled roughly

4,700 tiles per acquisition, the authors split the LAS data into 10–12 subsets; this minimized processing times and made files more manageable for desktop processing. The 2016 point cloud tiles had a complete file size of 368 gigabytes (GB) compressed (LAZ format), with an uncompressed point cloud tiles had a complete file size of 1,154.6 GBs, with an uncompressed file size of over 10 TBs. Once each processing iteration was complete, data were moved to a network-attached storage folder to free up local storage capacity for the next data subset.

BUILDING CLASSIFICATION AND FOOTPRINT CREATION

To correctly identify areas of tree canopy, we (the authors) had to be able to separate them from other objects of similar height, particularly buildings. Because the source data did not already have buildings classified, we needed to classify them from the point cloud ourselves to create a building footprint shapefile dataset; we used this dataset to remove buildings from our canopy cover outputs. We classified buildings using the “Classify LAS Buildings” tool available in the Esri ArcGIS Pro-3D Analyst toolbox. This study used the default parameters of 2 meters for minimum rooftop height and 6 square meters for minimum area. The tool goes through all LAS files in the LAS dataset to identify planar roof surfaces and reclassify them as class 6 (numeric code for buildings). This classification process can take multiple days depending on the density of the point cloud and computer processing power.

We only classified buildings in the 2018 data because the “Classify LAS Buildings” tool was unable to classify buildings in the 2016 data. The authors reported this issue to Esri in 2021, and believe it was due to the lower point density of the quality level 2 2016 acquisition (>2 pulses per m2 compared to >8). Due to time and funding constraints, as well as no clear technical solution, we were unable to classify buildings in the 2016 data. While we can use the 2018 building footprints to mask out buildings from the 2016 data, the data void areas in the two acquisitions are different. As a result, areas in the 2016 canopy cover data that

overlap with 2018 data voids do not have buildings removed. Manual removal of those buildings is possible, but we decided not to spend our limited budget on this task because the amount of time required to digitize those buildings outweighed the benefit of addressing this commission error. There are also changes in the built environment (both construction and demolition of structures in the roughly 2 years between acquisitions) that are not represented in the building footprint data, but it is difficult to determine how significant of an impact this may have on the 2016 canopy data.

Once the building classification was complete, we visually inspected the LAS dataset, symbolized by classification, to ensure the building classification was successful across the entire input dataset. We then used the “Make LAS Dataset Layer” tool to create a LAS dataset layer with only class-6 points (buildings) included. This layer was then input into the “LAS Point Statistics As Raster” tool, for which we set the “Method” to Most Frequent Class Code and the “Sampling Value” to 1. This resulted in a 1-meter-resolution raster displaying buildings. Finally, we used the “Raster to Polygon” tool with the “Simplify Polygons” parameter unchecked to create a building footprints shapefile. Because we noticed many buildings had a very small gap in the middle (1–2 pixels), we filled those gaps using the “Fill Holes” tool available in XTools, a commercial ArcGIS extension.

CANOPY HEIGHT PROCESSING AND THRESHOLDING

To create a canopy height model (CHM) raster, the authors first created a digital surface model (DSM). A DSM is a raster created from lidar first returns, using the first surface a lidar pulse reflects from to display the elevation above sea level. The first step of this process is to use the "Make LAS Dataset Layer" tool to create a layer with only first returns in classes 1 (Unassigned) and 2 (Ground). This is followed by inputting the data into the "LAS Dataset to Raster" tool, for which the "Value" field is set to Elevation, "Void Fill Method" is set to Simple, the "Sampling Type" is Cell Size, and the "Sampling Value" is set to 1. This produces a 1-meter-resolution DSM.

The next step is to use the Raster Calculator to subtract elevation values of the vendor-delivered DEM from the DSM elevation values to normalize values to aboveground heights and create the CHM. [Figure 7](#) shows examples of a DEM, DSM, and CHM for an area on the island of St. Croix in the U.S. Virgin Islands. Since the CHM represents the aboveground height of all features on the landscape (shrubs, trees, buildings, fences, etc.), we then focused on thresholding the height values to exclude all features below 2 meters, which can reasonably be considered noncanopy. We used the "Set Null" tool to set all values less than 2 to "no data" and all values ≥ 2 to 1, resulting in a single-class layer with values of 1 for pixels that have height greater than or equal to 2 meters.

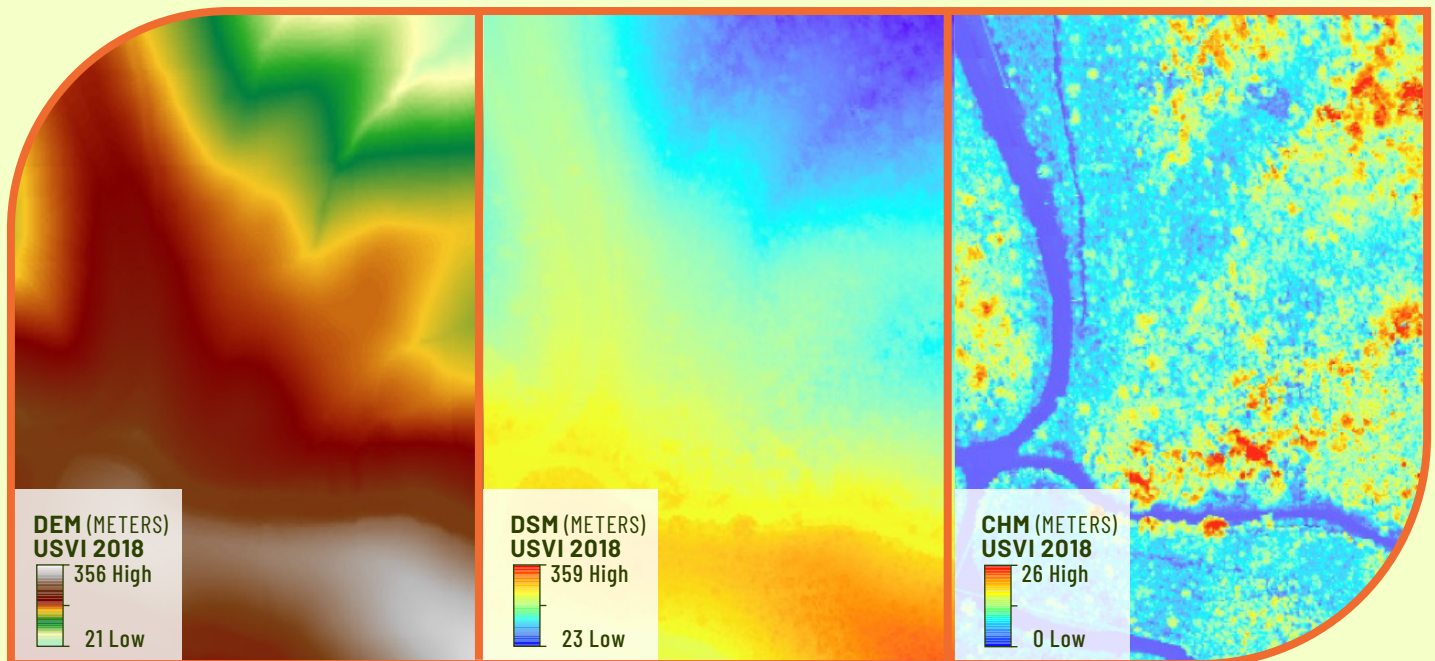


Figure 7.—Examples of a Digital Elevation Model (DEM), Digital Surface Model (DSM), and Canopy Height Model (CHM), St. Croix, U.S. Virgin Islands.

CANOPY COVER STATISTICS

To provide more meaningful information to land managers and the urban forestry community, we calculated the percent canopy cover for each municipality in Puerto Rico and each subdistrict in the U.S. Virgin Islands. To account for areas where data voids exist in the 2016 and 2018 canopy cover, we used the "Erase" tool to remove data void areas from the percent canopy cover calculations. Otherwise, the canopy cover percentages in those polygons containing data voids would be biased

and show a lower percent canopy cover. Next, we used the "Zonal Statistics As Table" tool to calculate the sum of canopy pixels within each polygon. Since each pixel is 1 m² with a value of 1 (canopy presence), the statistic equates to the total area of canopy within the polygon. Finally, we divided the total canopy cover area in each polygon by the total area of each municipality/subdistrict polygon (acquisition voids excluded).

ACCURACY ASSESSMENT

Assessing the overall accuracy of a map product is essential for reliable use. We performed an accuracy assessment on the 2016 and 2018 canopy cover layers, as well as on the 2018 building footprint shapefile. We followed internationally accepted practices for sample generation, photo interpretation, and accuracy assessment methods, following advice from Olofsson et al. (2014) and Stehman and Foody (2009). The process of conducting the accuracy assessment was composed of four steps: (1) initial preparation of the final data layers, (2) generation of a sample to be interpreted, (3) photo interpretation, and (4) analysis of the point data.

DATA PREPARATION

Most of the delivered data products are composed of single-class rasters or polygons (canopy cover = 1). This kind of data contains only the area covered by a class of interest, with all other areas considered "no data." This poses challenges for accuracy assessment, where it is necessary to identify both errors of omission (what has been left out) and commission (what has been erroneously included). To place points outside the class of interest, it was first necessary to convert the single class rasters into binary layers (canopy = 1, noncanopy = 0) that

The methods employed for the 2016 and 2018 canopy cover products were the same, but the implementation was different because of how the scope of this project progressed. Initially, we produced 2018 canopy cover data only for urban areas in Puerto Rico. Once we demonstrated the accuracy of the product in those urban areas, we chose to produce canopy cover data for the remaining nonurban areas in the 2018 data, as well as the complete 2016 acquisition. The 2018 canopy cover accuracy assessment results are divided into urban and nonurban areas for this reason.

covered the entirety of Puerto Rico and the U.S. Virgin Islands (2018 only), taking into account the actual footprints of the lidar acquisitions themselves (which, as previously mentioned, differed between 2016 and 2018). In brief, this process involved dissolving the lidar tile footprints for each acquisition into a single polygon, clipping them with the coastline of the island(s), and intersecting the resulting layers with the data products to produce a two-class raster.

PHOTO INTERPRETATION SAMPLE CREATION

For each of the three derived data products we created (2016 Canopy Cover, 2018 Urban Canopy Cover, and 2018 Nonurban Canopy Cover), we created a set of points to be photo-interpreted. A sample size of 1,000 points per product was chosen based on available resources and confidence interval considerations, as described in Foody (2009). Several thousand random sample points were generated for each class in each data layer, and then roughly 1,100 points (split between the two classes) were selected for each data layer to account for points that could not be interpreted for various reasons (clouds, missing imagery, etc.). The optimum number of samples to use for each class was estimated using

the methods from Wagner and Stehman (2015), using a Microsoft Excel spreadsheet provided from that study. This method uses the relationship between the areas of classes and an estimate of their expected errors to generate sample sizes that minimize the variance associated with the accuracy of a target class without under-representing other classes. In other words, this approach optimizes the sample distribution of a class of interest without sacrificing knowledge of the accuracy of any other classes, which is a compromise between area-balanced and equal class size random sampling approaches.

PHOTO INTERPRETATION

The photo interpretation of the various data layers produced was conducted by different team members using Esri ArcMap 10.7. The imagery used for the 2018 data layers was 4-band, visual, and near infrared data with a 15-centimeter resolution dating to 2019. This provided excellent coverage for the urban study area but had significant gaps in the

southeastern part of Puerto Rico (which were coincident with some, but not all, of the lidar data voids). The 2016 canopy data was interpreted using 8-band WorldView-2 imagery with a 2-meter resolution that was acquired in 2015 and 2016. [Table 2](#) outlines the number of points interpreted for each data product.

Table 2.—Photo interpreted points by data product

Data Product	Noncanopy (Nonbuilding points)	Canopy (Building points)	Total Points
2018 Urban Area	560	411	971
2018 Nonurban Area	463	523	986
2018 Building Data	855	178	1,033
2016 Canopy	447	631	1,078

ANALYSIS

We combined the results of the photo interpretation with the predicted values from the data layers and used them to produce a confusion matrix in R ([R Core Team, 2020](#)) using the confusion matrix function from the caret package ([Kuhn, 2020](#)).

Following the guidance provided by Stehman and Foody ([2009](#)) and Olofsson et al. ([2014](#)), this confusion matrix was then converted into an area-adjusted matrix and area-adjusted estimates of accuracy were performed in Microsoft Excel.



RESULTS

2016 AND 2018 CANOPY COVER PRODUCTS

The 2016 and 2018 canopy cover products ([figure 8](#)) are 1-meter-resolution rasters that display the presence of canopy cover across the full extent of the 2016 and 2018 lidar data acquisitions. These canopy cover products, the data void coverage

shapefiles, and percent canopy cover statistics by municipality/county subdistrict are available in an interactive [ArcGIS Online Viewer](#). The appendix of this report also provides percent canopy cover statistics by municipality/county subdistrict.



Figure 8.— Top: Urban area in San Juan, Puerto Rico with 2016 canopy cover. Bottom: 2018 canopy cover displayed

Because the 2016 and 2018 data voids have different extents, except for a small area of overlap, there are areas in the 2016 data where buildings have not been removed due to the lack of 2018 building footprints. In [figure 9](#), the top two images show a residential area along the east coast of Puerto Rico where data was acquired in 2016, but not in 2018. This results in the inclusion of numerous buildings in the 2016 canopy cover layer.

There are other known commission errors in the canopy layers from both years, including powerlines and other utilities, bridge features, railway cables,

and tall fences. The middle two images in figure 9 show some of these known commission errors in the 2016 and 2018 data. Powerlines are evident in both images, but to a lesser extent in the 2016 data. A power plant is evident in the upper left of each canopy cover layer, as are some bridge and railway features in the lower left of each image. While many of these powerline commission errors are present in both canopy data products, there appear to be consistently fewer of the long, thin linear features (e.g., fences, powerlines) in the 2016 canopy cover data (bottom two images). 2018 Building Footprints



Figure 9.—Top: Satellite imagery (left) of area along Puerto Rico's east coast where the 2018 building footprints are not available, resulting in commission errors of buildings in the 2016 canopy cover data classified as tree canopy (right). Middle: Area near San Juan where several commission error types are shown in 2016 (left) and 2018 (right), including powerlines and utilities, bridge features, and railway cables. Bottom: San Juan area where powerlines are evident in 2018 canopy cover data (right), but not in the 2016 canopy cover data (left).

The 2018 building footprints shapefile covers all of Puerto Rico and the U.S. Virgin Islands, except for where lidar could not be collected. [Figure 10](#) shows the building footprints in a neighborhood on

St. Thomas, U.S. Virgin Islands. The building footprints align well with the high-resolution imagery, and the buildings appear to be correctly delineated even in areas shadowed or obscured by vegetation.

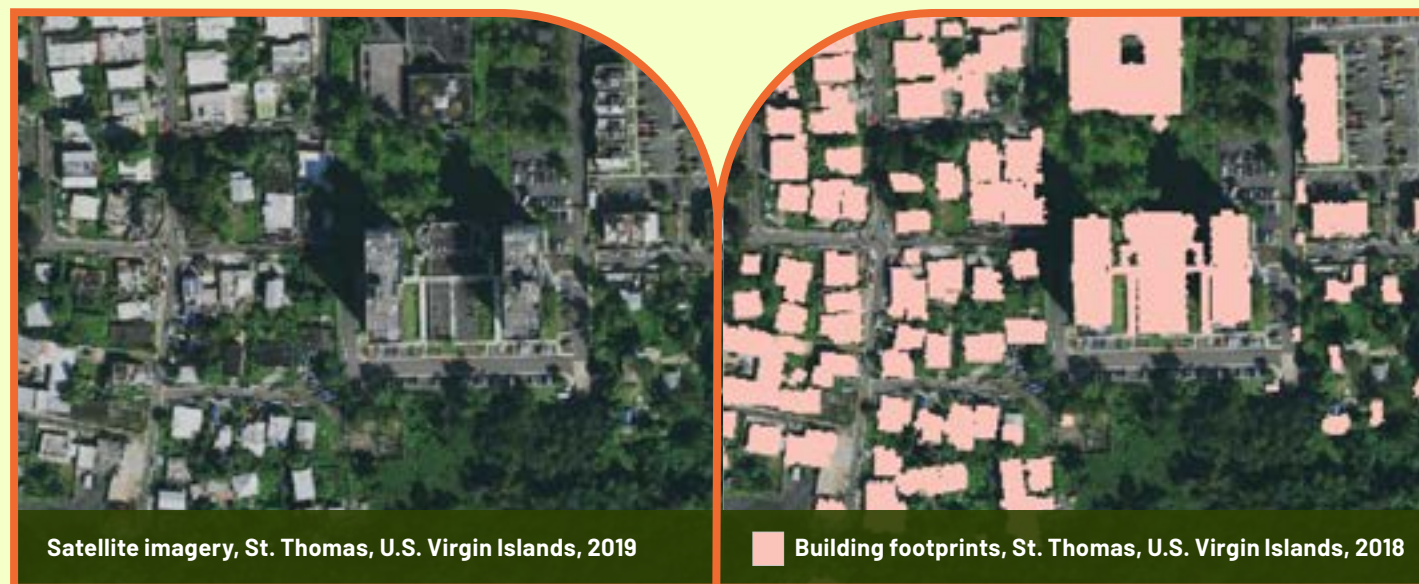


Figure 10.—High-resolution 2019 imagery (left) and 2018 building footprints (right) in a residential area on St. Thomas, U.S. Virgin Islands.

CANOPY HEIGHT DATA

To produce canopy cover layers, this study also created several canopy height models (CHMs). These models provide valuable datasets for myriad applications. Because of this, the study authors

mosaicked the CHMs for each processing subset and provided them as a final product. These CHMs are 32-bit rasters ([figures 11 and 12](#)) with large file sizes—40 GB for 2016 and 43 GB for 2018.

ACCURACY OF THE CANOPY AND 2018 BUILDING FOOTPRINT PRODUCTS

Each data product that had an accuracy assessment has a set of accuracy and area metrics associated with it. These metrics measure distinct aspects of the accuracy of the data. The overall accuracy represents how much of the study area was correctly labeled. The producer's accuracy measures how often areas that belong to a particular class were correctly labeled as belonging to that class and is the complement of errors of omission. The user's accuracy measures how often the class label applied to an area is correct and is the complement of errors of commission. [Table 3](#) shows the overall accuracy for each layer, while [tables 4–9](#) show the producer's and user's accuracy for

each respective product, along with adjusted area estimates for each cover class. It is important to note that these tables present accuracy in terms of area, not in terms of sampled points. This means the accuracies have been adjusted to reflect the relative areas of the classes, which means they provide the likelihood a given area is labeled correctly in the final map. This can have some slightly counterintuitive influence on the overall accuracy numbers. For instance, overall accuracy can look very high if a class with a large area is labeled correctly most of the time, even if classes with small areas are much less accurate in their labeling.

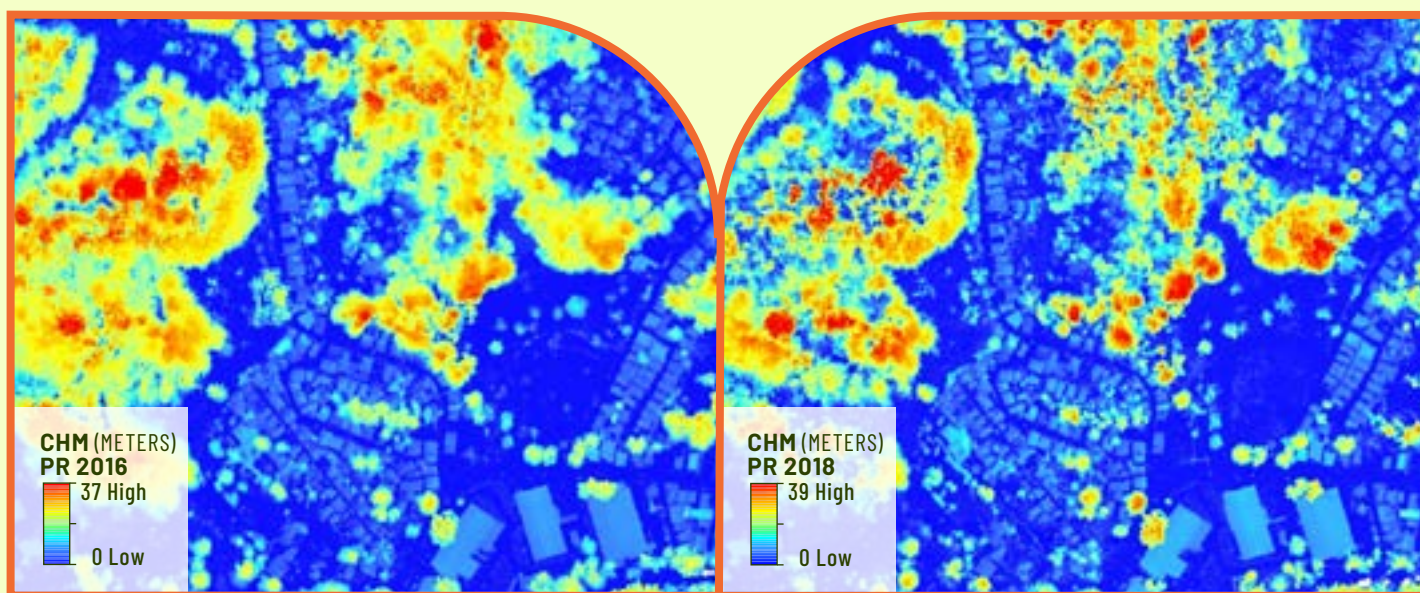


Figure 11.—Canopy height models (CHMs) in meters for 2016 (left) and 2018 (right) in a neighborhood in Mayagüez, Puerto Rico.

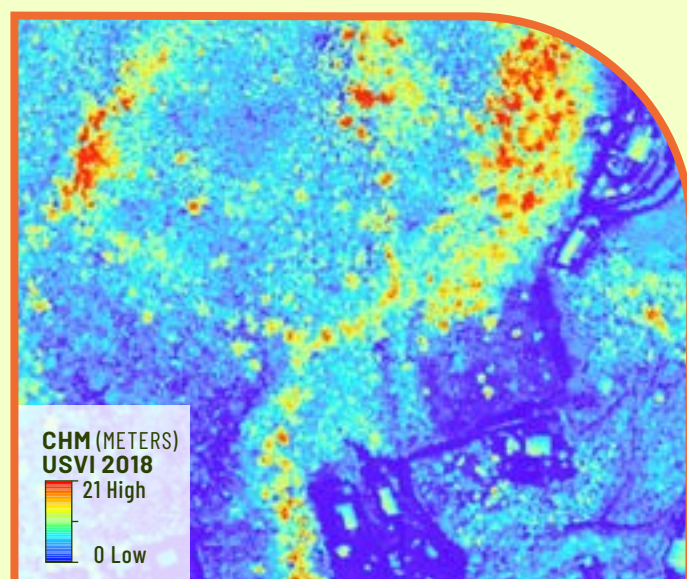


Figure 12.—Canopy height model (CHM) in meters for 2018, St. Croix, U.S. Virgin Islands.

Table 3.—The overall accuracies for all the data products produced.

Data Product	Overall Accuracy
2016 Canopy Layer	98.98%
2018 Building Footprint Layer	98.82%
2018 Urban Canopy Cover Layer	97.03%
2018 Nonurban Canopy Layer	96.43%

DISCUSSION

The workflow outlined in this report produced very accurate canopy cover and building footprints using only lidar and Forest Service enterprise software. Due to the nature of lidar data, the authors expected the map to be extremely accurate, and this proved to be the case with all products having an overall accuracy greater than 90 percent. Only the producer's accuracy of building footprints class falls below this 90-percent threshold at 80.3 percent, reflecting a comparatively large amount of omission. Errors of omission and commission for the canopy layers appear to be in the range of 4–6 percent for all data products.

However, the study authors expected some false positives and omissions in the canopy layers due to an inability to comprehensively remove powerlines and other previously identified commission errors in urban areas. This section will mainly focus on how these inaccuracies can be addressed in the future and how the underlying lidar data influenced the commission errors.

Table 4.—Canopy data product: User and producer accuracies

2016 Accuracy	Noncanopy	Canopy
User's Accuracy	98.88%	99.05%
Producer's Accuracy	98.73%	99.16%

Table 6.—Urban Canopy data product: User and producer accuracies

2018 Accuracy	Noncanopy	Canopy
User's Accuracy	98.53%	94.16%
Producer's Accuracy	97.01%	97.08%

Table 8.—Building Footprint data product: User and producer accuracies

2018 Accuracy	Noncanopy	Canopy
User's Accuracy	99.17%	89.53%
Producer's Accuracy	99.60%	80.30%

One benefit of the lower density 2016 point cloud data is fewer powerlines are captured in the canopy cover layer. The denser 2018 acquisition captures significantly more powerlines, but both products generally do not include the smaller powerlines connecting to individual buildings. This was expected because quality level 1 lidar data will generally produce more detailed representations of buildings, vegetation, and other prominent urban features due to the significantly higher pulse density.

To improve the canopy cover data products, manual editing would be required to accurately remove known commission errors such as powerlines, bridges, and industrial areas. Semiautomated workflows will struggle to remove linear features without inadvertently removing canopy cover, and any such approach would require visual inspection and manual editing to address errors. More advanced deep learning approaches could potentially be used to accurately remove errors like powerlines from canopy layers, but these approaches require large

Table 5.—Canopy data product: Estimate of areas.

2016 Estimate of Areas	Noncanopy	Canopy
Area (ha)	375,673	503,422
Standard error (ha)	2,700	2,700
95% Confidence Interval (ha)	5,292	5,292

Table 7.—Nonurban Canopy data product: User and producer accuracies

2018 Accuracy	Noncanopy	Canopy
User's Accuracy	93.84%	98.80%
Producer's Accuracy	98.62%	94.59%

Table 9.—Urban Canopy data product: Estimate of areas

2018 Estimate of Areas	Noncanopy	Canopy
Area (ha)	232,554	115,359
Standard error (ha)	1,796	1,796
95% Confidence Interval (ha)	3,520	3,520

training sets that are time consuming to produce. It is also likely that the overall area of the powerline-associated errors is quite small and is more visually impactful than a meaningful bias in the estimate of the area of the urban canopy.

Another avenue for improving the canopy cover and building footprint datasets would be to produce rasters at a higher resolution than 1 meter, as demonstrated by MacFaden et al. (2012), who produced rasters with 1-foot spatial resolution. There are pros and cons to this approach. Deriving canopy cover from higher resolution DEMs and CHMs would likely produce more precise representations of both canopy and buildings. However, this would significantly increase processing time and data storage requirements, and it would not be appropriate for sparser quality level 2 or lower lidar acquisitions. Higher resolution products would also be more likely to capture more commission errors than the 1-meter products.

The other known issue with the datasets is related to the data voids in the two acquisitions, which was outside of the author's control. These areas where lidar data could not be collected experience persistent cloud cover; the available high-resolution imagery products for Puerto Rico also include large data voids in the heavily forested areas on the east side of the island. While the data voids prevented this study from mapping canopy cover and buildings in certain areas, they should not compromise urban canopy cover data to any significant extent because the voids are located primarily over forested, rural areas of Puerto Rico.

The difference in areal extent of the data voids meant that 2016 canopy data has significant commission error from buildings. However, future

end users of the data could download the 2016 point cloud data and test new versions of the "Classify LAS Building" tool or other building delineation methods to create building footprints for these areas and reduce that error. The alternatives to this would be the manual digitization of buildings or the use of deep learning tools to classify building extents using lidar and potentially imagery. Another possibility would be to use alternative building footprint data. While the [Microsoft Global ML Building Footprints](#) dataset covers Puerto Rico and the U.S. Virgin Islands, the datasets are temporal composites (2014–2022). This is problematic in creating a canopy map as it would require significant effort to reconcile mismatches in buildings caused by differences in time between data products.

CONCLUSION AND NEXT STEPS

This project set out to use recently collected lidar data covering Puerto Rico and the U.S. Virgin Islands to map canopy cover at a high resolution, enabling the identification of canopy down to the level of individual street trees. The resulting products include a canopy presence raster for 2016 and 2018, canopy height rasters for 2016 and 2018, and a 2018 building footprints shapefile. Methods outlined in this report are intended to provide detailed guidance that can be replicated for any other urban canopy cover mapping effort.

Although final data products contain visible commission errors in urban areas, these errors are minimal and do not significantly impact percent canopy cover estimates. The accuracy of these products proved to be very high and there are clear paths outlined in this report to improve the datasets for future projects. The Forest Service's Geospatial Technology and Applications Center has made final deliverables available for download via an [ArcGIS Online web map viewer](#).

A key next step is to build awareness of these data products and the workflow outlined in this report. With the data easily accessible, it will be important to get the data in the hands of researchers and land managers in Puerto Rico and the U.S. Virgin Islands who could integrate the data into existing programs of work. Because the study produced data across the full extent of each acquisition and included canopy height datasets for each year, efforts to build awareness should extend beyond the urban forestry community to the variety of stakeholders that could benefit from detailed high-resolution canopy height and cover data. These datasets can be incorporated into change detection workflows aimed at assessing the impacts of past and future hurricanes on canopy cover. Moreover, lidar data is now available across most of the United States at quality level 2 or higher, and this workflow could be replicated in urban areas across the country to produce accurate urban canopy cover data.

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CANOPY COVER PERCENTAGE STATISTICS BY PUERTO RICO MUNICIPALITY AND U.S. VIRGIN ISLANDS COUNTY SUBDIVISION

2016 PUERTO RICO CANOPY COVER

Municipality/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
Puerto Rico (includes Vieques and Culebra)	8864.95	56.47	1275.46	27.08
Adjuntas	173.78	78.28	2.78	42.91
Aguada	80.08	47.55	14.99	33.69
Aguadilla	94.65	38.31	40.43	26.50
Aguas Buenas	77.95	69.56	4.01	46.95
Aibonito	81.17	63.19	9.58	37.82
Añasco	102.55	58.53	10.04	28.04
Arecibo	328.38	55.81	41.84	26.71
Arroyo	38.91	53.84	6.94	22.26
Barceloneta	48.54	38.11	15.28	34.32
Barranquitas	88.79	55.52	4.63	42.86
Bayamón	115.29	40.76	66.36	22.50
Cabo Rojo	187.02	33.24	23.54	25.39
Caguas	152.98	58.53	47.56	28.40
Camuy	120.21	52.03	10.01	29.97
Canóvanas	85.48	56.00	15.17	24.13
Carolina	122.52	37.23	52.53	19.64
Cataño	13.23	18.17	10.82	17.33
Cayey	134.58	61.73	15.77	33.37
Ceiba	76.04	63.41	8.37	33.74
Ciales	172.77	83.61	3.10	40.75
Cidra	94.42	50.53	12.18	34.52
Coamo	202.09	59.25	11.74	32.15
Comerío	73.88	67.90	2.59	37.16
Corozal	110.28	59.68	6.09	38.71

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

2016 PUERTO RICO CANOPY COVER

Municipality/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
Culebra	30.94	62.85	0.47	22.43
Dorado	60.37	38.34	18.49	32.17
Fajardo	78.86	53.91	17.72	29.72
Florida	39.43	71.78	3.62	43.36
Guánica	96.41	49.84	4.78	34.52
Guayama	169.98	47.42	16.51	20.73
Guayanilla	109.72	69.78	5.50	31.44
Guaynabo	71.59	49.83	35.25	29.55
Gurabo	73.33	51.04	18.21	27.90
Hatillo	108.25	42.58	16.35	23.48
Hormigueros	29.36	35.42	8.77	31.31
Humacao	116.43	42.14	28.48	31.33
Isabela	143.58	58.20	18.37	21.00
Jayuya	115.34	76.93	2.96	39.57
Juana Díaz	157.17	52.20	17.61	30.98
Juncos	68.93	47.31	14.59	31.11
Lajas	156.68	28.75	5.54	31.74
Lares	159.64	71.24	3.62	44.03
Las Marías	120.45	83.22	0.70	42.97
Las Piedras	87.78	48.89	15.20	36.35
Loíza	51.84	40.98	9.03	25.83
Luquillo	67.05	64.55	5.51	27.55
Manatí	119.27	53.20	22.30	36.70
Maricao	94.86	86.28	0.60	44.03
Maunabo	54.50	69.28	2.64	25.66
Mayagüez	200.16	55.64	32.96	31.28
Moca	130.44	56.87	10.55	36.90
Morovis	100.81	61.95	8.89	39.57
Naguabo	134.04	58.57	5.48	22.86
Naranjito	71.87	58.88	2.59	45.14
Orocovis	165.17	69.22	2.16	36.55
Patillas	122.02	75.04	2.69	26.94

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

2016 PUERTO RICO CANOPY COVER

Municipality/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
Peñuelas	115.97	70.85	10.38	34.96
Ponce	302.81	63.92	60.14	24.95
Quebradillas	60.01	52.69	8.83	25.19
Rincón	36.87	55.37	4.41	28.35
Río Grande	157.64	65.24	14.73	26.86
Sabana Grande	92.83	65.71	6.36	29.35
Salinas	181.31	33.97	14.80	22.08
San Germán	141.20	67.18	10.59	36.83
San Juan	127.62	31.14	105.11	24.88
San Lorenzo	137.80	60.49	7.99	32.56
San Sebastián	184.45	53.59	7.69	30.01
Santa Isabel	88.83	23.25	7.07	14.32
Toa Alta	71.38	47.27	22.13	30.89
Toa Baja	60.85	26.08	32.47	24.67
Trujillo Alto	55.38	50.08	21.21	34.96
Utua	298.02	75.15	5.50	39.06
Vega Alta	71.75	59.60	15.68	38.00
Vega Baja	120.56	51.23	26.14	33.19
Vieques	133.48	71.89	2.82	43.89
Villalba	95.92	65.56	6.88	43.78
Yabucoa	143.11	49.28	8.23	27.97
Yauco	178.00	71.91	12.99	30.46

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

2018 PUERTO RICO CANOPY COVER

Municipality/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
Puerto Rico (includes Vieques and Culebra)	8864.95	45.44	1186.13	21.71
Adjuntas	173.78	64.69	2.78	29.04
Aguada	80.08	37.25	14.99	23.55
Aguadilla	94.65	29.48	40.43	19.14
Aguas Buenas	77.95	57.79	4.01	39.71
Aibonito	81.17	53.17	9.58	29.31
Añasco	102.55	49.85	10.04	23.25
Arecibo	328.38	47.71	41.84	19.86
Arroyo	38.91	47.22	6.94	18.17
Barceloneta	48.54	28.65	15.28	23.61
Barranquitas	88.79	46.23	4.63	35.17
Bayamón	115.29	31.98	66.36	18.90
Cabo Rojo	187.02	27.01	23.54	22.41
Caguas	152.98	44.76	47.56	20.62
Camuy	120.21	44.51	10.01	22.82
Canóvanas	85.48	38.80	15.17	18.30
Carolina	122.52	26.49	52.53	14.83
Cataño	13.23	18.67	10.82	17.10
Cayey	134.58	63.84	15.77	15.58
Ceiba	76.04	43.62	8.37	13.23
Ciales	172.77	65.99	3.10	25.33
Cidra	94.42	43.09	12.18	25.11
Coamo	202.09	48.95	11.74	19.83
Comerio	73.88	59.65	2.59	29.64
Corozal	110.28	42.92	6.09	26.31

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

2018 PUERTO RICO CANOPY COVER

Municipality/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
Culebra	30.94	49.53	0.47	17.48
Dorado	60.37	30.76	18.49	23.94
Fajardo	78.86	40.13	17.72	22.95
Florida	39.43	59.44	3.62	31.17
Guánica	96.41	37.15	4.78	26.60
Guayama	169.98	52.16	16.51	20.80
Guayanilla	109.72	59.02	5.50	24.77
Guaynabo	71.59	38.23	35.25	23.87
Gurabo	73.33	34.92	18.21	15.50
Hatillo	108.25	36.00	16.35	16.95
Hormigueros	29.36	29.73	8.77	24.90
Humacao	116.43	30.36	28.48	21.85
Isabela	143.58	50.84	18.37	14.86
Jayuya	115.34	61.76	2.96	25.85
Juana Díaz	157.17	39.67	17.61	19.50
Juncos	68.93	32.57	14.59	18.39
Lajas	156.68	21.85	5.54	29.24
Lares	159.64	55.89	3.62	27.27
Las Marías	120.45	68.07	0.70	25.03
Las Piedras	87.78	33.22	15.20	17.88
Loíza	51.84	26.83	9.03	18.46
Luquillo	67.05	51.77	5.51	24.94
Manatí	119.27	42.78	22.30	25.78
Maricao	94.86	71.64	0.60	32.25
Maunabo	54.50	55.83	2.64	18.29
Mayagüez	200.16	42.63	32.96	24.80
Moca	130.44	44.89	10.55	26.45
Morovis	100.81	45.63	8.89	25.61
Naguabo	134.04	30.87	5.48	17.89
Naranjito	71.87	43.67	2.59	33.13
Orocovis	165.17	57.67	2.16	25.86
Patillas	122.02	64.91	2.69	22.53

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

2018 PUERTO RICO CANOPY COVER

Municipality/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
Peñuelas	115.97	64.36	10.38	29.34
Ponce	302.81	54.77	60.14	20.22
Quebradillas	60.01	44.28	8.83	17.11
Rincón	36.87	48.32	4.41	22.67
Río Grande	157.64	48.10	14.73	22.14
Sabana Grande	92.83	55.98	6.36	24.28
Salinas	181.31	30.54	14.80	17.80
San Germán	141.20	60.95	10.59	33.42
San Juan	127.62	22.98	105.11	18.48
San Lorenzo	137.80	46.38	7.99	21.31
San Sebastián	184.45	40.68	7.69	19.20
Santa Isabel	88.83	17.93	7.07	8.44
Toa Alta	71.38	38.07	22.13	25.46
Toa Baja	60.85	24.38	32.47	22.30
Trujillo Alto	55.38	33.81	21.21	25.40
Utua	298.02	61.76	5.50	25.90
Vega Alta	71.75	50.06	15.68	29.04
Vega Baja	120.56	43.45	26.14	25.88
Vieques	133.48	51.40	2.82	27.28
Villalba	95.92	52.63	6.88	28.59
Yabucoa	143.11	38.52	8.23	20.19
Yauco	178.00	58.25	12.99	23.93

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

2018 U.S. VIRGIN ISLANDS CANOPY COVER BY ISLAND AND COUNTY SUBDISTRICT

Island/ Territory (green)	Area (km ²)	Canopy Cover Percentage	Urban Area (km ²)*	Urban Canopy Cover Percentage
St. Croix	216.27	44.56	41.69	23.56
Christiansted subdistrict	1.96	26.48	1.85	25.81
Frederiksted subdistrict	3.62	30.01	1.83	23.85
Northwest subdistrict	47.25	61.59	1.29	27.56
Southwest subdistrict	14.92	20.12	5.78	18.58
East End subdistrict	34.53	42.08	0.71	29.08
Northcentral subdistrict	32.87	57.14	1.96	22.80
Southcentral subdistrict	32.84	27.51	16.73	18.43
Anna's Hope Village subdistrict	25.67	35.45	1.55	32.95
Sion Farm subdistrict	24.34	46.89	9.99	32.37
St. John	49.74	65.55	1.94	39.58
Coral Bay subdistrict	4.94	51.18	1.92	39.53
Cruz Bay subdistrict	7.26	51.39	N/A	N/A
East End subdistrict	2.45	30.52	N/A	N/A
Central subdistrict	36.71	70.51	1.92	46.41
St. Thomas	71.26	18.67	10.82	17.10
Charlotte Amalie subdistrict	8.72	22.26	7.84	21.47
East End subdistrict	13.71	38.24	5.42	28.89
Water Island subdistrict	2.53	38.78	0.00	14.56
Northside subdistrict	27.45	55.98	4.52	44.29
Southside subdistrict	11.46	47.27	4.03	40.72
Tutu subdistrict	3.97	29.65	3.55	26.80
West End subdistrict	13.48	65.39	N/A	N/A

*Urban areas used in this analysis were defined using the [Martinuzzi et al. 2007](#) methodology.

LIST OF ACRONYMS

Acronym	Meaning
C-CAP	Coastal Change Analysis Program
CHM	Canopy height model
DEM	Digital elevation model
DSM	Digital surface model
FIA	Forest Inventory and Analysis
GIS	Geographic information system
GTAC	Geospatial Technology and Applications Center
IITF	International Institute of Tropical Forestry
NAIP	National Agriculture Imagery Program
NLCD	National Land Cover Dataset
NOAA	National Oceanic and Atmospheric Administration
NUCFAC	National Urban and Community Forestry Advisory Council
USGS	U.S. Geological Survey

Forest Service, U.S. Department of Agriculture
International Institute of Tropical Forestry (IITF)
Geospatial Technology and Applications Center (GTAC)