

Mapping the Diversity of Agricultural Systems in the Cuellaje Sector, Cotacachi, Ecuador Using ATL08 for the ICESat-2 Mission and Machine Learning Techniques

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Abstract. The mapping of cropland helps to make decisions due to the intensification of its use, where the conditions of the crops change due to climatic variability and other socio-economic factors. In this way, the implementation of modern sustainable agriculture is essential to prevent soil degradation as measures to guarantee food security, propose sustainable rural development and protect the provision of different ecosystem services associated with the soil. NASA's Ice, Cloud, and Land Elevation Satellite-2 (ICESat-2) launched September 15, 2018, offers new possibilities for the mapping of global terrain and vegetation. An additional science objective is to measure vegetation canopy height as a basis for estimating large-scale biomass and biomass change. The Advanced Topographic Laser Altimeter System (ATLAS) instrument on-board ICESat-2 utilizes a photon-counting LIDAR and ancillary systems (GPS and star cameras) to measure the time a photon takes to travel from ATLAS to Earth and back again and to determine the photon's geodetic latitude and longitude. ICESat-2 ATL08 (Along-Track-Level) data product is developed for vegetation mapping with algorithms for along-track elevation profile of terrain and canopy heights retrieval of the from ATLAS point clouds. Thus, this study presents a brief look at the ATL08 product highlight the broad capability of the satellite for vegetation applications working with data of study area Seis de Julio de Cuellaje (SDJC), province of Imbabura, Ecuador. The study used Normalized Difference Vegetation Index (NDVI) by the year 2020 time-series at 30 m resolution by employing a Machine Learning (ML) approach. The results of this research indicate that the ATL08 data from the ICESat-2 product provide estimates of canopy height, show the potential for crop biomass estimation, and a machine learning land cover classification approach with a precision of 95.57% with Digital Elevation Model (DEM) data.

Keywords: ICESat-2 · ATLAS · Altimetry · Canopy height · LIDAR · Sentinel-2 · NDVI · Machine learning · Cropland

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1 Introduction

In the sector of Seis de Julio de Cuellaje (SDJC), the production and commercialization dynamics during the years 2015–2020 has revolved around the production and commercialization of three emerging crops: granadilla, naranjilla, and tree tomato, however, it is evident that one of the main problems faced by producers is due to the lack of technical knowledge about the weather conditions and the use of the soil to improve the production of these fruit trees. An important challenge to consider in the next decade is the appropriate use of the agricultural potential of Ecuador, this involves building an agricultural productive zone with updated cartographic information on the suitability of the soil, use of microclimates depending on the altitude of the land to establish the most economically important crop, support the efforts of the different producers to promote their integration, find better participation schemes to strengthen their development, achieve greater benefits in this important activity in the agricultural sector and, above all, determine the profitability that they have received. generated as a community.

Therefore, there is a need for regular mapping using satellite images with adequate spatial/temporal precision and resolution, generated regarding the crop's phenological stage and regional meteorological data. Users can track plant growth regularly by comparing maps from different dates. Governmental programs such as NASA's ICESat-2 [1] are taking significant efforts to make such data freely available with the intention to fuel innovation and entrepreneurship [2]. With access to such data, applications in the domains of agriculture, disaster recovery, climate change, urban development, or environmental monitoring can be realized [3]. The ICESat-2 mission has the goal of monitoring changes in the cryosphere, it is equipped with a high precision laser that provides routine measurements of the vegetation canopy height and also performs very high-resolution surface measurements around the world, to a wide range of terrestrial applications [4]. The ICESat-2 spacecraft provides power, propulsion, navigation, thermal control, data storage, handling, ground communication, and orbit control for ATLAS, the mission's height-measuring instrument. ICESat-2 in numbers: use ellipsoid WGS84, orbit repeats every 91 days, it is at an altitude of about 500 km, has an inclination of 92°, covers up to 88° N & S at a speed of 7 km/s, the precision of flight time of a single photon is 800 ps, has 6 beams organized in 3 pairs, each beam of 90 m across the track, 3.2 km separating the pairs, diameter of the illuminated spot less than 17.5 m, the aperture diameter of the telescope of 0.8 m, 532-nm laser wavelength, 10-kHz pulse repetition rate, 1.5 ns transmitted pulse width, has 4 Solar panels average of 1320 W, onboard data recorder stores 580 gigabits/day, X-band downlink sends 220 Mbits a second [5]. ATLAS can take measurements every 0.7 m along the satellite's ground path. The ICESat-2 produces geophysical products over various surface types: inland water (ATL13), oceans (ATL12), atmosphere (ATL09), land/vegetation (ATL08), sea ice (ATL07), and land ice (ATL06) [6]. More information regarding the ICESat-2 mission can be found at https://icesat-2.gsfc.nasa.gov/.

In recent times, Machine Learning (ML) algorithms like Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANN) have been used by researchers to classify satellite data and its derivatives into crop types. Feng [7] successfully used spectral bands, texture parameters, vegetation indices, and phenological parameters derived from Sentinel-2 time-series data as inputs to RF and SVM classification algorithms. They examined the use of short-wave infrared (SWIR) and water vapor bands of Sentinel-2 data for differentiating between crops [8]. Convolution Neural Network (CNN) bagged unprecedented accuracy in a variety of fields—object-based satellite image classification is one such application that proliferated in recent times. While high-resolution satellite image, required for object-based classification is not available for free, researchers often rely on freely available mid-resolution data (e.g. Landsat—each pixel represents a 30 m * 30 m land parcel). The mechanism of CNN elucidates that it considers the neighboring pixels and relies on the pattern and texture of it, and not just one pixel at a time [14]. In the land cover classification of mid-resolution satellite data (e.g. Landsat), the objective is to classify each pixel, based on its digital number (DN) values across different bands. In this post, we investigate the usability of the CNN model on mid-resolution data, where object-identification is neither possible nor the goal.

The objective of this research is to review the data dictionary for product ATL08 using an ICESat-2 transect over a vegetated region of SDJC, providing a quantitative evaluation of the recoveries of canopy and terrain height compared to observations of selected ecosystems to highlight the satellite's broad capacity for vegetation applications.

2 Methods and Materials

2.1 Overview of the Research Region

The study area is located in Imbabura province, Cotacachi region, parish "Seis de Julio de Cuellaje" in Ecuador (see Fig. 1.a.b) that lies between 0°23′15″ N and 0°24′26″ N latitudes and 78°32′35″ W and 78°30′31″ W longitudes. The parish SDJC is one of the 8 rural parishes of the Cotacachi canton, located in the southwestern part of the Intag area. It is 70 km 200 m from the city of Cotacachi, 71 km 200 m from Otavalo, 95 km 200 m from Ibarra, and 183 km 200 m from Quito, capital of Ecuador [10]. SDJC has a climate that ranges from temperate to very rainy sub temperate, depending on the altitude levels that range from 1750 m.a.m.s.l. to 2600 m.a.m.s.l. It has a climate that varies between 18 °C and 23 °C with average annual precipitation rainfall ranging from 1000 mm to 3000 mm (see Fig. 1.c). The soils are fine-silty [11], mixed, and mesic (see Fig. 1.d). The environmental conditions are favorable for agriculture, and cropland is the dominant land use class in the study site.

The main crops that are developed in the parish of SDJC are the tree tomato and the passion fruit in the first place, and the second place the cultivation of beans and naranjilla. The giant variety tree tomato is the main product of the parish, followed by the passion fruit, which has had an important rise in recent times. The bean variety one thousand one with a planted area of approximately 134 hectares, an important average production, and the naranjilla, white carrot with 6 hectares; the aforementioned crops are sown in monocultures or associated crops [12]. Approximately 27% of the population of the parish is dedicated to agriculture.

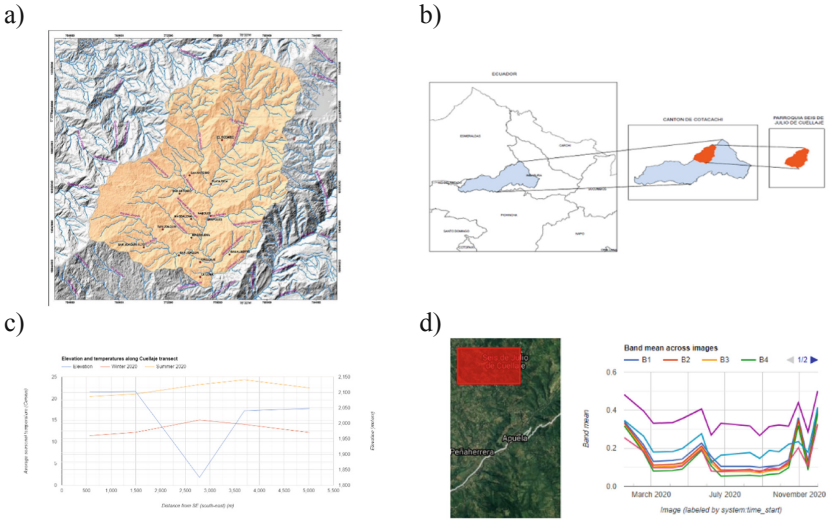

Fig. 1. a) Map location of the study area SDJC; b) map relative to the national, cantonal, and parish level of area of interest; c) elevation and temperatures along Cuellaje transect; d) band mean across images Landsat 8. Source: own study.

The naranjilla (solanum quitoense) is a fruit native to the subtropical understory of the Andes of Ecuador and grows mainly in places with good humidity, cool and shady regions around 800 and 1400 m.a.s.l. The cultivation of this fruit is highly important both nationally and internationally, due to the nutritional properties of both smell and color that make it a perfect fruit for agribusiness, as it allows the production of ice cream, preserves, jams, refreshing drinks, among other products [13].

2.2 Data

We collected Operational Land Imager (OLI) images present on the Landsat 8 satellite with less than 50% cloud cover from the United States Geological Survey (USGS) [29] between 01/01/2020 and 12/31/2020.

The large number of data points that ICESat-2 collects, coupled with the small size of the laser footprint of approximately 17 m [9], will mean that you will have information about changes in elevation measurements for a particular area. This, in turn, will allow a better understanding of the current situation and better predict how much the canopy level will increase and the impacts on vegetation [14]. The ATL08 algorithm was developed specifically for the extraction of ground heights including canopy height, canopy cover percentage, surface slope, roughness, and apparent reflectance from the ATL03 photon cloud data [15], for each beam presented along-track, which typically contain more than 100 signal photons. All ICESat-2 ATL08 data products were acquired from https://nsidc.org/data/atl08 [16]. This data set (ATL08) download contains an along-track (see Fig. 2).

2.3 ICESat-2 Data Processing

Laser pulses from ATLAS illuminate three left/right pairs of spots on the surface that as ICESat-2 orbits Earth trace out six ground tracks that are typically about 14 m wide. Each ground track is numbered according to the laser spot number that generates it, with ground track 1L (GT1L) on the far left and ground track 3R (GT3R) on the far right. The ATL08 data product is organized by ground track, with ground tracks 1L and 1R forming pair one, ground tracks 2L and 2R forming pair two, and ground tracks 3L and 3R forming pair three. Pair tracks are approximately 3 km apart in the across-track direction [17].

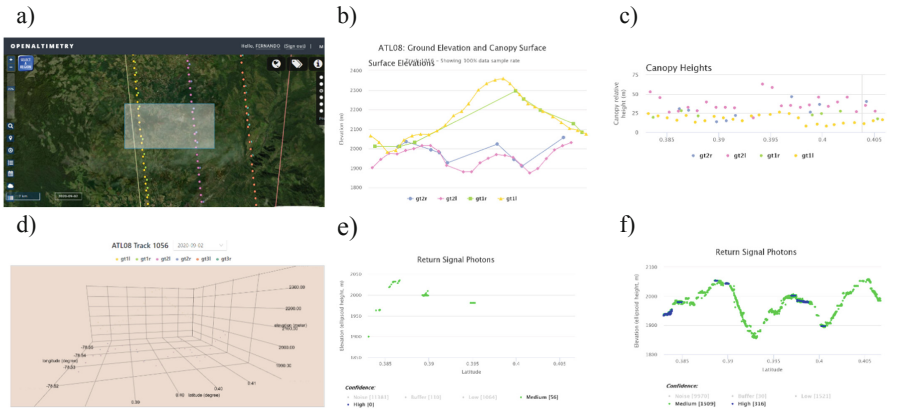

Fig. 2. a) ICESat-2 ATL08 transects (GT1R and GT2R) showing tracks over the extent of SDJC within the study site; b) ATL08: ground elevation and canopy surface; c) canopy heights; d) ATL08 track 1056 graph 3D; e) return signal photons: track ID: 1056 - beam: gt2r - showing 100% data sample rate; f) return signal photons: track ID: 1056 - beam: gt2l - showing 100% data sample rate. Source: own study.

The objective is to highlight the potential of ICESat-2 for the mapping of vegetation in three ecosystems: Montane evergreen forest, piemontan forest, xerophilous montane scrub present in the site of Cotacachi and provide a quantitative assessment of the accuracy of terrain and canopy height retrievals for the area of interest of SDJC. For this, the ATL08 software has been designed to accept multiple approaches to capture both the upper and lower surface signal photons. The algorithm utilizes iterative photon filtering in the along-track direction, which best preserves signal photons returned from the canopy and topography while rejecting noise photons [19]. To access the ATL08 product data dictionary and be able to establish an iterative photon filtering method along the track to preserve the topography and capture noble photons, while rejecting noise photons, thus having enough photons from both the canopy as off the ground [20], we use the icepyx [30] Python software library, which works with the ICESat-2 dataset, using OpenAltimetry for data discovery and NSIDC's Application Programming Interface (API). Photons that are reflected from the top of the canopy in vegetated areas are not always flagged as a signal. As such, before surface finding commences in ATL08, the input from ATL03 is passed through an additional signal finding method referred to as DRAGANN (Differential, Regressive, and Gaussian Adaptive Nearest Neighbor), which was developed specifically to identify and remove noise photons from histogrammed photon point clouds [17].

To generate a reference map for the study site encompassing the nearby ICESat-2 transect, Above Ground Biomass (AGB) [21] estimates from SDJC were aggregated to 30 m pixels, matching Landsat pixels. AGB was the dependent variable in a random forest (RF) regression model developed with input variables from NDVI from Landsat imagery. NDVI and enhanced vegetation index (EVI) was calculated for each image and combined with 2020 SDJC canopy cover and SDJC land cover as independent variables in the RF [22] model. The RF model was built and applied to generate the reference AGB map for the study site, using the Python over Euro Data Cube [23] (Cloud API to most important Earth Observation datasets) and Google Platform: Cloud, Colab, Earth Engine, and Drive [24]. This is a supervised, regression machine learning problem. During training, we give the RF both the features and targets and it must learn how to map the data to a prediction. Moreover, this is a regression task because the target value is continuous (as opposed to discrete classes in classification).

3 Results

The methodology adopted aims at predicting the crop yield of SDJC by providing the required dataset from that area. It involves the following steps:

1) Collection of the dataset ICESat-2 ATL08 and Landsat 8: In this step, we first create an ICESat-2 DAAC Data Access with the desired search parameters and download data from the NSIDC [28], we must first authenticate ourselves using a valid Earthdata login. This will create a valid token to interface with the DAAC as well as start an active logged-in session to enable data download. The token is attached to the data object and stored, but the session must be passed to the download function. Then we can order the granules (see Fig. 3).

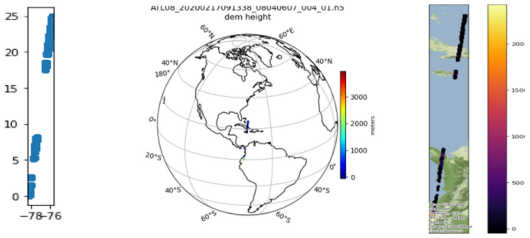

Fig. 3. ICESat-2 measurement plot on the surface showing the 2 laser beam pairs. Each beam pair contains a strong and weak beam. The relative positions of the beams on the surface provides the capability to determine regional and local surface slope. Source: own study developed python code. Source: own study developed python code.

2) Pre-Processing of data 2: Performing the pre-processing on the satellite image for extraction of data features for further analysis. Convert data into geopandas data frame, which allows for doing basing geospatial operations.
3) Deciding crop patterns with help of data filter points based on DEM extent: Use point cloud alignment techniques to align DEMs to points, we can use the transformation matrix to inform on the horizontal and vertical offset between ICESat-2 tracks and DEMs (see Figs. 4 and 5).

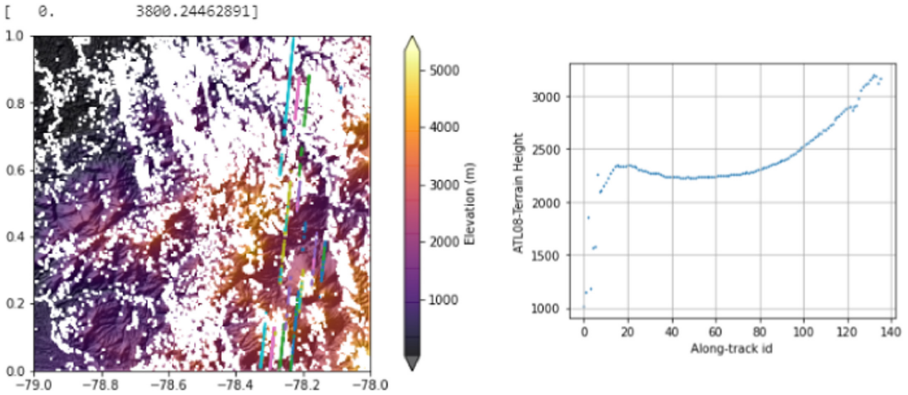

Fig. 4. ATL08 canopy top elevations plotted of the SDJC study site. Vertical offset between ICESat-2 tracks and DEMs. The area is a mix of urban, and forested landscapes on gently rolling terrain. Source: own study developed python code.

4) Applying the machine learning for accurate results: This is the step where we used TensorFlow, Keras, and machine learning algorithm given by Random Forest model so we can get high accurate identification. We will be using a flavor of the Iterative Closest Point alignment algorithm, implemented in NASA Ames Stereo Pipeline (ASP) [25] (see Fig. 6).

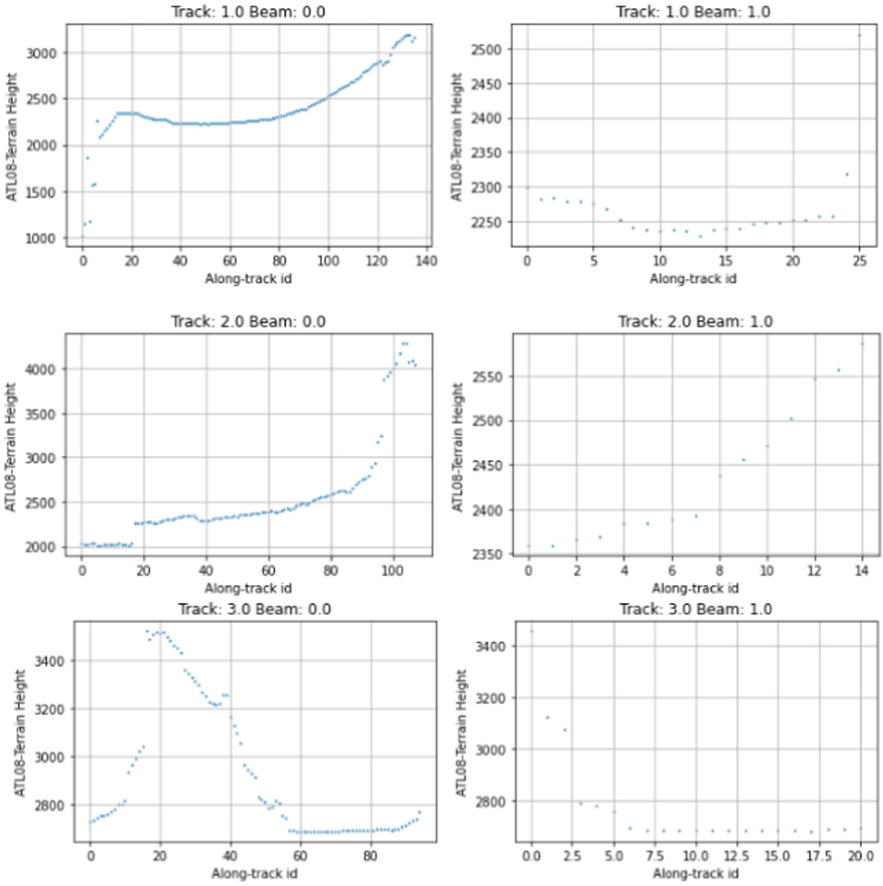

Fig. 5. ATL08 canopy heights were plotted against relative height metrics in SDJC. Source: own study developed python code.

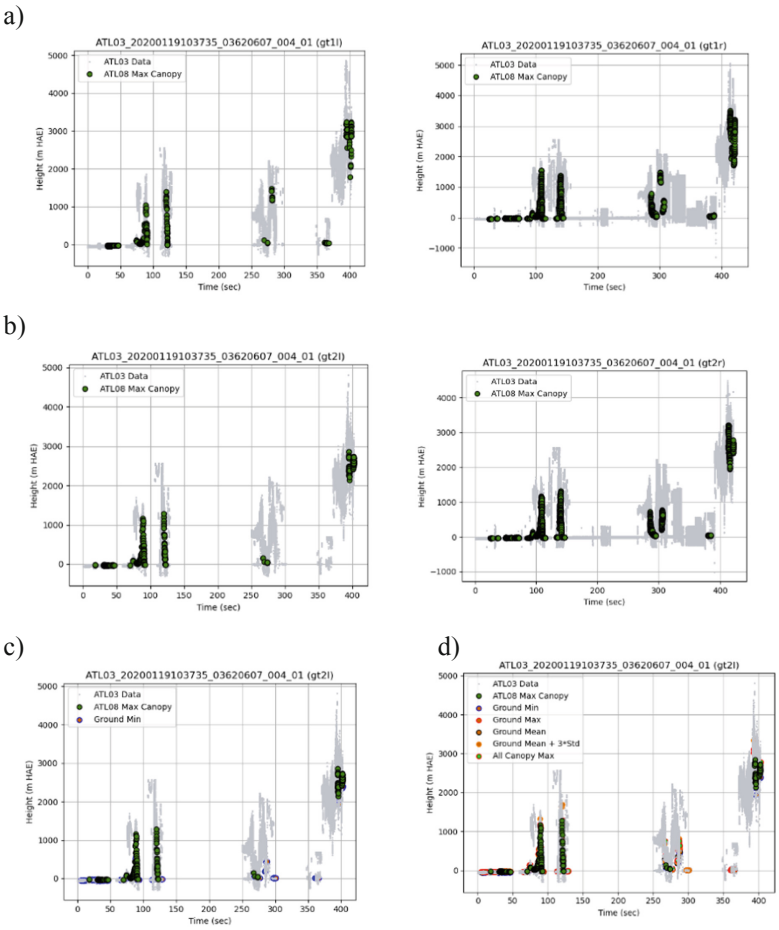

Fig. 6. a) Filtered and classified data from GT1L and GT1R max Canopy ATL08; b) Filtered and classified data from GT2L and GT2R max Canopy ATL08; c) filtered and classified data from GT2L max canopy ATL08, ground min; d) filtered and classified data from GT2L max canopy ATL08, ground min; ground max, ground mean, ground mean + 3Std, all canopy max. Granule ID ATL08_20200119103735_03620607_004_01.h5. Source: own study developed python code.

4 Conclusions

This study has shown that the combination of ICESat2 ATL08 and DEM data can support the measurement of the composition of a cropped landscape to complement the use of satellite remote sensing to achieve some of the food productivity improvement goals. Therefore, crop mapping requires the development of new algorithms for the recovery of the land surface and the height of the canopy. Given the fact that commercial satellites with the high spatial resolution are becoming more affordable for remote sensing users, this study has the potential to support ongoing operational land and vegetation product programs which can benefit from these strategies/scheme for estimate yields, and the

increased availability of new, large geospatial datasets on soils, management, and the weather should also benefit future efforts in this area.

Although the cost or availability of satellite data with sufficient spatial resolution to discriminate agricultural fields was an obstacle in the past, this barrier is rapidly diminishing. Improved algorithms to pre-process remote sensing data and estimate yields, and the increased availability of new, large geospatial datasets on soils, management, and the weather should also benefit future efforts in this area.

This research proposes a land cover classification approach using RF with remote sensing data and DEM. Given the sheer volume of altimetry data from ICESat-2, the is huge potential in extracting insights from the data with machine learning that were not possible before. Keep in mind that machine learning is a big field and here we focus on only a few specific approaches and a few computational tools. Additionally, DEM is very helpful for land cover classification. The final overall accuracy of the proposed approach is 95.57%. However, there are still some shortcomings. Compared with ground truth, the outline of ground objects in the final result is still not accurate enough, which should be solved in future research. According to the Chunked Dataset (canopy_h_metrics) found in ATL08_20200119103735_03620607_004_01.h5, which describes the height metric based on the cumulative distribution of canopy heights over the interpolated soil surface, and the Chunked Dataset (h_te_best_fit) that best fits the location of the midpoint of each 100m segments, a slope correction and weighting is applied to each ground photon based on the distance at the height of the slope at the center of the segment, in both fragments, the relationship between the photons of the canopy and the total number of signal photons, in each outgoing laser shot on the ecosystems of the area of interest produces the apparent density of the branches and leaves of the canopy; thus biases the canopy cover estimate high.

The advantage of using ICESat-2 with the ATLAS ATL08 micro-pulse, multi-beam instrument, is known global terrain elevation, global canopy heights, and global canopy coverage at resolutions ranging from 30 m to 100 m, along with data hyperspectral and multispectral it is possible to quantify the above-ground biomass of the vegetation of the ecosystems of the SDJC area, thus being able to improve agricultural production.

Crediting photographs and images:*Imagery from the NASA ICESat-2 instrument, courtesy of NASA NSIDC DAAC.*

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