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ForestAz - Using Google Earth Engine and Sentinel data for forest monitoring in the Azores Islands (Portugal)

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Abstract

Aim of study: ForestAz application was developed to (i) map Azorean forest areas accurately through semiautomatic supervised classification; (ii) assess vegetation condition (*e.g.,* greenness and moisture) by computing and comparing several spectral indices; and (iii) quantitatively evaluate the stocks and dynamics of aboveground carbon (AGC) sequestrated by Azorean forest areas.

Area of study: ForestAz focuses primarily on the Public Forest Perimeter of S. Miguel Island (Archipelago of the Azores, Portugal), with about 3808 hectares.

Materials and methods: ForestAz was developed with Javascript for the Google Earth Engine platform, relying solely on open satellite remote sensing data, as Copernicus Sentinel-1 (Synthetic Aperture Radar) and Sentinel-2 (multispectral).

Main results: By accurately mapping S. Miguel island forest areas using a detailed species-based vegetation mapping approach; by allowing frequent and periodic monitoring of vegetation condition; and by quantitatively assessing the stocks and dynamics of AGC by these forest areas, this remote sensing-based application may constitute a robust and low-cost operational tool able to support local/regional decision-making on forest planning and management.

Research highlights: This collaborative initiative between the University of the Azores and the Azores Regional Authority in Forest Affairs was selected to be one of the 99 user stories by local and regional authorities described in the catalog edited by the European Commission, the Network of European Regions Using Space Technologies (NEREUS Association), and the European Space Agency (ESA).

Additional key words: Sentinel-1; Sentinel-2; Copernicus; Vegetation Indices; Forest Mapping; Forest Management; Aboveground Carbon

Abbreviations used: AGC (Aboveground Carbon); ARFI (Azorean Regional Forest Inventory); BSI (Bare Soil Index); CART (Classification and Decision Tree); DRRF (Azores Regional Authority in Forest Affairs); ESA (European Space Agency); GEE (Google Earth Engine); GIS (Geographical Information Systems); GRD (Ground Range Detected); LULC (Land Use / Land Cover); NBR (Normalized Burn Ratio); NDVI (Normalized Difference Vegetation Index); NDWI (Normalized Difference Water Index); NEREUS (Network of European Regions Using Space Technologies); NPCI (Normalized Pigment Chlorophyll Ratio Index); RF (Random Forests); SAR (Synthetic Aperture Radar).

Authors' contributions: MFU developed the Javascript-based ForestAz's Google Earth Engine application. AG conceived the application's idea, reviewing and validating every stage of its development and design with MFU. Both authors developed the final manuscript.

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Introduction

Getting a better comprehension of the effects of forests in the carbon cycle and climate change requires to accurately monitor forest resources in shorter periods of time (Wittke *et al.,* 2019). Carbon is stored in living biomass by photosynthesis and returned to the atmosphere through the processes of respiration, decomposition, and combustion. Anthropogenic activities can alter carbon levels in these systems by facilitating the release or storage of carbon in different carbon pools (IPCC, 2000). It is well known the critical role of forests to mitigate climate change due to their contribution through their carbon sink and carbon storage properties (Calado *et al.,* 2015).

The Azorean Regional Forest Inventory (ARFI) is the primary forest planning and management tool in this archipelagic Portuguese and European Union's Outermost Region. Until 2020, it has also been the most widely used

Land Use / Land Cover (LULC) map in the Azores Autonomous Region (Portugal), being mostly used for forestry policies and spatial planning by local and regional authorities. Through the combination of Geographical Information Systems (GIS) based on on-screen photo-interpretation of very-high spatial resolution aerial imagery from 1998 (black and white) and 2007 (natural color), and exhaustive field campaigns for survey and validation (Gil *et al.,* 2014), the current ARFI version was produced in 2007 by the Azores Regional Authority in Forest Affairs (DRRF). Because the overall cost of this methodological procedure is very high (in terms of both human, logistics, and data resources) and time-consuming, periodic updates to this cartographic product are not performed as frequently as needed for spatial planning and forest management purposes (Gil *et al.,* 2018).

In order to overcome these limitations, the creation of a remote sensing framework based on Google Earth Engine (GEE) (Gorelick *et al.,* 2017) entitled ForestAz app was proposed to: (1) accurately map Azorean forest areas using semiautomatic supervised classification; (2) assess vegetation condition (*e.g.,* greenness and moisture) by computing and comparing several spectral indices; and (3) quantitatively assess the stocks and dynamics of aboveground carbon (AGC) sequestrated by Azorean forest areas. ForestAz app was developed to constitute a robust and low-cost operational tool to support local/regional decision-making on forest planning and management.

To our knowledge, ForestAz constitutes the first GEE-based operational tool directly developed for local/regional authorities to increase their workflow's cost-effectiveness in forest mapping and assessment for planning and management purposes. In fact, GEE is becoming a game-changer tool for supporting forest sciences (Jahromi *et al.,* 2021), and several works effectively used multi-source and multi-resolution GEE-based approaches for forest classification/mapping (*e.g.,* Kaplan, 2021; Li J *et al.,* 2021; Li R *et al.,* 2021) and forest assessment, including aboveground biomass and carbon estimations (*e.g.,* Sánchez-Ruiz *et al.,* 2019; Venkatappa *et al.,* 2020; Feyen *et al.,* 2021).

Material and methods

The Azores Islands are located in the North Atlantic and are an archipelago consisting of nine volcanic islands. São Miguel, the largest (74677 hectares) and most populated island (about 133 thousand inhabitants) within the Azores archipelago, is located about 1500 km from mainland Europe (centroid coordinates: X: 632351.58 m., Y: 4182515.23 m., UTM WGS84 26N). The Public Forest Perimeter is located in the eastern part of S. Miguel Island, characterized by steep areas with slopes higher than 20% and including the island's highest point, Pico da Vara, with 1105 meters of altitude (Gil, 2005).

ForestAz focuses primarily on the Public Forest Perimeter of S. Miguel Island (Archipelago of the Azores, Portugal), with about 3808 hectares.

The ForestAz application

In this section, every current function of the Google Earth Engine-based "ForestAz App" (Fig. 1) is described, and its potential results aiming at mapping, assessing, and monitoring forest areas in S. Miguel Island (Azores, Portugal) are demonstrated, namely regarding data selection, data processing, supervised classification, results' analysis, and visualization. The methodology is organized to clearly comprehend the whole computational workflow followed by this GEE-based application developed with Javascript, publicly available at https://manuferu.users.earthengine.app/view/forestaz. In addition, all the code and layers used along with a user guide describing step by step how to access the data can be found at: https://github.com/Manuferu/ForestAZ.

Selection of remote sensing datasets

This application was designed to rely mostly on open satellite remote sensing data, as Copernicus Sentinel-1 (Synthetic Aperture Radar) and Sentinel-2 (multispectral). Sentinel-2 Multispectral Instrument (MSI) Level-2A imagery collection was downloaded by Google and ingested in the GEE API. It was atmospherically corrected and orthorectified using the sen2cor algorithm (Main-Knorn *et al.,* 2017) before its ingestion to GEE. All available Sentinel-2 images within GEE were taken into account. Two different filter options were developed to make an optimized selection: a) date; b) cloud coverage. The application has the option to define the time range for the images search and selection. On the other hand, it has the option to complement and add cloud cover search. All this filtering procedure is performed by the algorithm by querying the metadata attributes. Although one of the major drawbacks is the frequent cloud coverage over the archipelago, the high temporal resolution of the image acquisition may mitigate the impact of this issue (Gil *et al.,* 2012). A cloud filter option was added to the application to address this issue (*e.g.,* "Maximum cloud cover: 20 %"). However, the most relevant disadvantage of this method is the measurement of cloud coverage at the full-scene level, which could mislead the user regarding the cloud presence over the specific study area (a subset of the image). Thus, we masked out all the cloud and cirrus coverage in the available imagery to mitigate this problem.

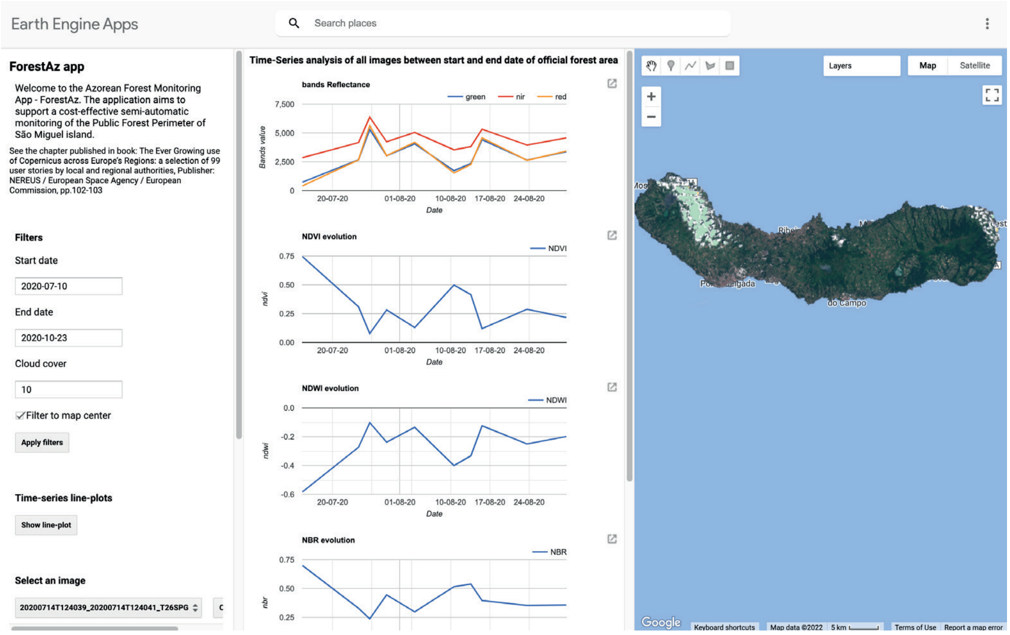

Figure 1. Overview of the ForestAz app Graphical User Interface. Left panel shows all the filtering options as well as the list of images filters in scroll down option. At the center, the dashboards with line plots of different vegetation indices and bands. On the visualization part, the island of S. Miguel, with the normalized difference vegetation index (NDVI) applied and clouds masked out.

Sentinel-1 Synthetic Aperture Radar (SAR) Ground Range Detected (GRD) C-band log scaling was used for this project. Each scene was preprocessed using the Sentinel-1 toolbox (Veci *et al.,* 2014) through the following steps: thermal noise removal; radiometric calibration; and terrain correction using Shuttle Radar Topography Mission (SRTM). In addition, due to the abrupt topography of S. Miguel Island, we have introduced a further change from GRD to ARD (Analysis Ready) data by performing border noise correction, speckle filtering, and radiometric terrain normalization to mitigate radiometric distortions caused by topography (Mullissa *et al.,* 2021).

Computation of vegetation indices-based monitoring

Empirical studies have demonstrated the correlation between vegetation indices and vegetation parameters (Freitas *et al.,* 2005; Glenn *et al.,* 2008; Sun *et al.,* 2019). In addition, they have been shown helpful for vegetation condition assessment meanwhile have set a standardization to vegetation dynamics interpretation (Schultz *et al.,* 2016). ForestAz is especially focused on characterizing and representing the patterns followed by man-planted forests and woody invasive plants patches to support forest planning and management in the Azores islands. To achieve this goal, some of the most representative and widely used vegetation indices (Xue & Su, 2017) were selected, namely the normalized difference vegetation index (NDVI; Rouse *et al.,* 1974; Tucker, 1979; Bannari *et al.,* 1995), the normalized difference water index (NDWI; Gao, 1996), the normalized burn ratio (NBR; Key *et al.,* 2002), the normalized pigment chlorophyll ratio index (NPCI; Main *et al.,* 2011), and the bare soil index (BSI; Rasul *et al.,* 2018). This application considers vegetation indices mapping and visualization as an early-stage explanation of forest cover change assessment. Therefore, it provides a dashboard showing the maps and line plots of all vegetation indices, allowing them to be compared (Fig. 2).

Forest type classification with Sentinel data

Sentinel-2 spectral bands 2-8 and 10-12 spectral were used in the classification workflow. Bands 2, 3, 4 and 8 had a spatial resolution of 10 m. Although the other bands had lower spatial resolution, a 10 m spatial resolution constituted the reference for the processing of ForestAz app products. Combining both SAR and optical remote sensing data can perform well as it might constitute an advantage for classification tasks, leading to better mapping accuracy (Yuan *et al.,* 2020; Mngadi *et al.,* 2021; Singh & Tiwari, 2021). In general terms, the main benefit of integrating both optical and radar imagery for classification purposes lies in the fact of synergistically combining multispectral information and structural properties (Joshi *et al.,* 2016). Since the ForestAz application works with one single Sentinel-2 image at a time, the workflow implemented to integrate both optical and SAR data was to look for the Sentinel-1 image closest in time to the selected

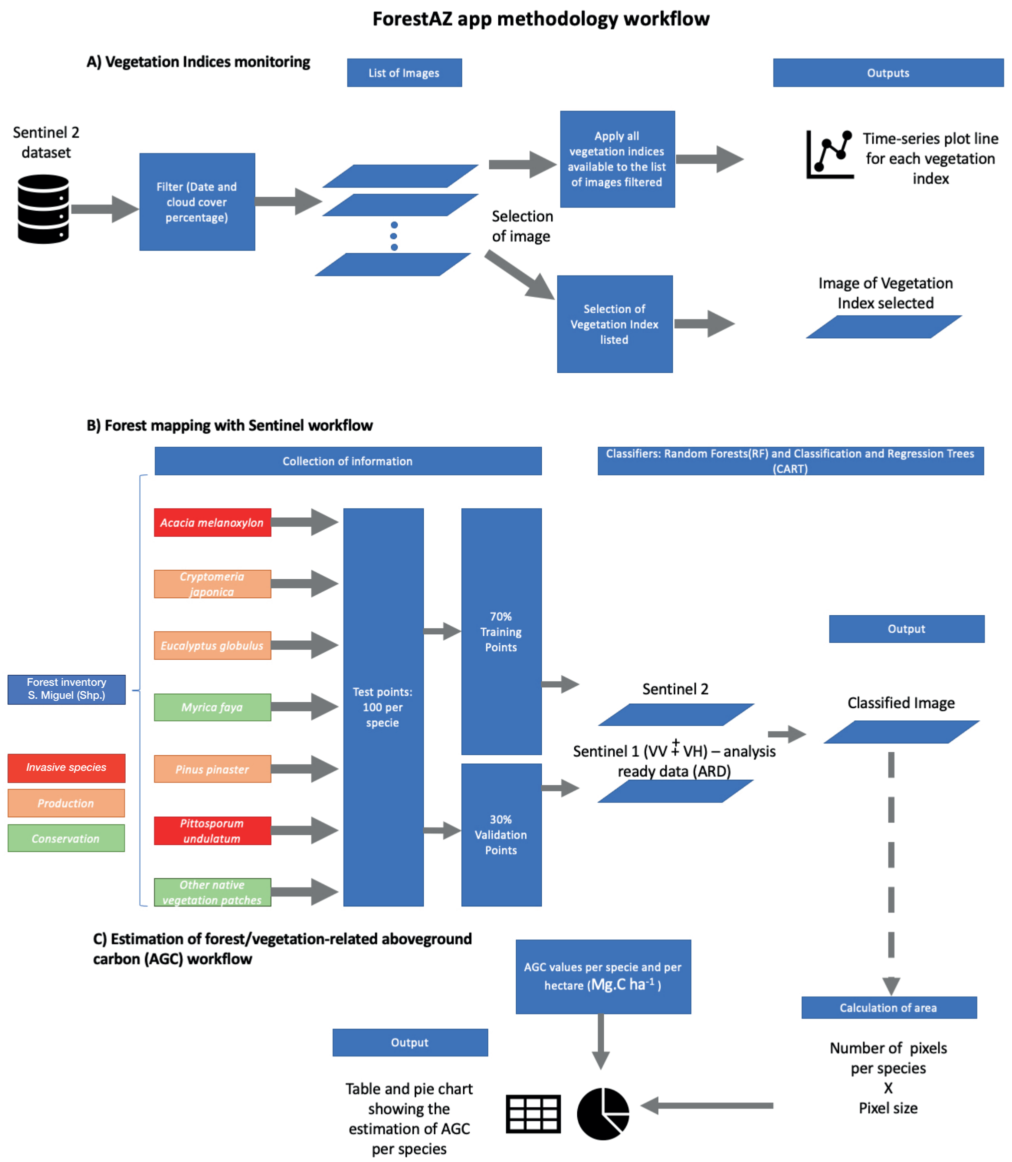

Figure 2. A) Vegetation indices monitoring methodological workflow. B) Forest mapping with Sentinel-based methodological workflow. C) Methodological workflow for estimating forest/vegetation-related aboveground carbon (AGC) stocks.

Sentinel 2 image. Once the algorithm identifies the most comparable SAR image, it grabs the "VV" and "VH" bands from Sentinel-1 and adds these to the Sentinel-2 image previously selected by the user (Fig. 2).

A key aspect of the application was the supervised classification. The aim of this supervised classification was not only to map forest areas (at the forest species/patch level) within the selected case study area ("Public Forest Perimeter") but also to provide information on the amount of AGC amount sequestrated by these forest covers, to support decision-making in forest planning and management. To perform and evaluate different classification methods, we implemented and tested two of the most used classification methods: Random Forests (RF) and Classification and Decision Tree (CART). Those classifiers are available at GEE API. CART is a non-parametric pattern recognition-based classification method. It builds and identifies a decision tree using training data to find the correct classification accuracy (Breiman, 2011). On the other hand, RF makes predictions using a set of CARTs. The trees are created using a bagging approach, allowing the classifier to select several times the same sample, while others may not (Belgiu & Dragut, 2016). The way the classifiers build trees and separates node by node is part of the GEE API.

From the current Azores Regional Forest Inventory version, we identified seven main categories of forest/vegetation cover (Fig. 2). We created an averaged sample of 100 stratified random points per class to be ingested into the GEE asset repository, based on GIS-based photo-interpretation of the most recently available aerial imagery and fieldwork validation.

The accuracy of a classifier refers to the probability of correctly classifying the set of points randomly taken

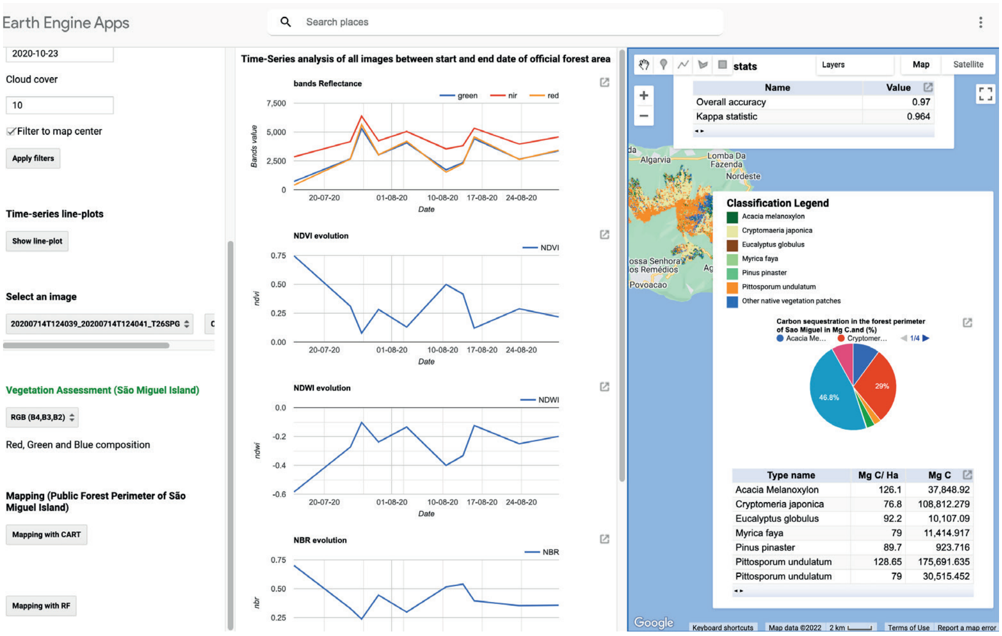

Figure 3. Examples of outputs provided by the ForestAz app: Vegetation indices time-series evolution and comparison between two dates; classifier stats (upper-center); forest mapping and aboveground carbon (AGC) assessment in Mg C ha^{-1} and % (lower right).

(Foody, 2002). To avoid one of the main concerns while using classifiers, we split the number of points into training points and validation points, with a proportion of respectively 70% as model training points and 30% as validation points. The accuracy assessment of the classification maps is always performed by computing overall and "per class" user accuracy and producer accuracy, using only the validation datasets (Congalton & Green, 2019).

Estimation of forest/vegetation-related AGC

Developing and testing straightforward, low-cost, and effective remote sensing-based operational approaches able to mapping, assessing, and monitoring forested/vegetated AGC stocks are paramount to support decision-making in land and forest planning and management in small oceanic islands (Massetti & Gil, 2020).

The values of AGC per hectare (Mg C ha^{-1}) for each forest/vegetation category mapped in the ARFI (for S. Miguel Island), introduced below, were obtained according to the reviews made for Macaronesian forests (Madeira Island – Archipelago of Madeira; and S. Miguel Island – Archipelago of the Azores) by Calado *et al.* (2015) and Massetti & Gil (2020), namely: *Acacia melanoxylon*, 126.1 Mg C ha^{-1}; *Cryptomeria japonica,* 76.8 Mg C ha^{-1}; *Eucalyptus globulus,* 92.2 Mg C ha^{-1}; *Myrica faya,* 79 Mg C ha^{-1}; *Pinus pinaster,* 89.7 Mg C ha^{-1}; *Pittosporum undulatum,* 128.65 Mg C ha^{-1}; other native vegetation patches, 79 Mg C ha^{-1}.

Taking the values listed above (per species and hectare), ForestAZ calculates the area per species by multiplying the total number of pixels mapped for a specific class in the forest cover map to the respective pixel area (100 m²). By running the code, there will be an automatic generation of tables and graphs with AGC values for the "Public Forest Perimeter" area (Fig. 2C).

Results and discussion

The Google Earth Engine-based ForestAz app is available online at https://manuferu.users.earthengine.app/view/forestaz. The code and further description of contents and methodology can be found at https://github.com/Manuferu/ForestAZ and can be freely accessed, modified, and improved to be used in other geographical areas contexts. The code is designed to paste it straight forward to GEE's playground.

Vegetation indices mapping and time series evolution

By accurately mapping S. Miguel island forest areas using a detailed species-based vegetation mapping approach (instead of a standard and generic LULC mapping approach), and by allowing frequent and periodic monitoring of vegetation condition (*e.g.,* greenness and moisture), ForestAz will allow forest managers accessing relevant information and comparing different patterns in a dashboard layout for a more targeted and accurate assessment.

Fig. 3 shows an example of an NDVI run in a Sentinel-2 image. In addition, it shows the generated time-series line plots within the same period of time of three different vegetation indices. As it is represented, all this information is displayed together, making it possible to change the vegetation index to visualize and see the evolution of all vegetation indices available in the application simultaneously.

Forest mapping and AGC pie chart and tables

By quantitatively assessing the stocks and dynamics of AGC sequestrated by these forest areas, this remote sensing-based application constitutes a robust and low-cost operational tool able to support local/regional decision-making on forest planning and management (*e.g.,* allowing more targeted and less random on-site assessment, monitoring, conservation/restoration, and law enforcement measures).

Fig. 3 shows an example of forest mapped using CART classifier along with a pie chart where the forest managers will have a clear picture of the different quantities of AGC sequestrated by species. In addition, an additional table was generated by the application to display results, including the information above mentioned of the amount of sequestrated AGC stocks per species per hectare, along with the total quantity. Once the user takes the option of either classifier, the AGC pie chart and tables are automatically generated and displayed in the console section of the application.

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