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Estimation of Tree Height in Burned Areas with GEDI Laser Data in Northern Portugal and Galicia (Spain)

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Abstract: We analyzed the tree height of four areas affected by wildfires in northern Portugal and Galicia (Spain), using the GEE platform, random forest regression model and GEDI data. Before the fires the height varied from 5.21 to 20.16 meters, with r^2 values of 0.82 and 0.67. After the fires, heights of 5.55 to 9.12 meters were recorded, with values of r^2 0.47 and 1. These r^2 values after fires indicate the absence or limitation of sample data. We conclude that the GEDI data has great potential to assist in the mapping of areas affected by Wildfires.

Keywords: Wildfires; Remote Sensing; GEDI; Sentinel; Random Forest

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1. Introduction

Large wildfires constitute a very significant disturbance on fire prone landscapes. In different locations around the world, such as California (USA), Portugal, Spain and Australia, the intensity of these natural events is enhanced by the effects of climate change and overexploitation by the population of natural resources [1–5].

Wildfires are events that result in great loss of biodiversity, in addition to important changes in the surface where they occur [6,7]. Portugal is a country where the recurrence of forest fires is increasing due to a combination of environmental and human factors, such as drier years, with climatic conditions favourable to their propagation, such as lack of precipitation, low humidity and wind. Considering the human factor, in the last three decades, the unequal distribution of the population throughout the Portuguese territory is related to the regional distribution of ignition sources [8]. The same scenario is observed in the northwest region of Spain.

The consequences of the fires are of social and economic order, affecting rural properties and their agricultural production, resulting in a significant loss of capital and of environmental order, degrading landscape natural values and decreasing the provision of ecosystem services. The forest is responsible for providing different ecosystem services such as carbon storage in vegetation and soil, food, water filtration, and climate regulation at local and regional levels. With the increase in the occurrence of wildfires, the availability of ecosystem services is altered [9].

In the context of climate change, quantifying carbon stocks, an important ecosystem service to mitigate global warming, is essential. To quantify the carbon stock, biophysical parameters such as the height of the trees are necessary. To measure this parameter, there is the possibility of using a worldwide database Global Ecosystems Dynamics Investigation (GEDI), a LIDAR instrument on board the International Space Station that has made data available since April 2019, with a scan diameter of 25 m. This instrument makes high-resolution observations of the vertical structure of the forest, providing metrics needed to understand processes and patterns of biodiversity [10]. The studies of

[11–13] used GEDI data to estimate the height of trees in forests. We used the Google Earth Engine platform to analyze satellite imagery, digital elevation model and GEDI data to measure vegetation height before and after fires.

2. Material and method

2.1. Study area

The study was performed in 4 areas affected by wildfires in the summer of 2020 in northern Portugal and Galicia (Spain) (figure 1).

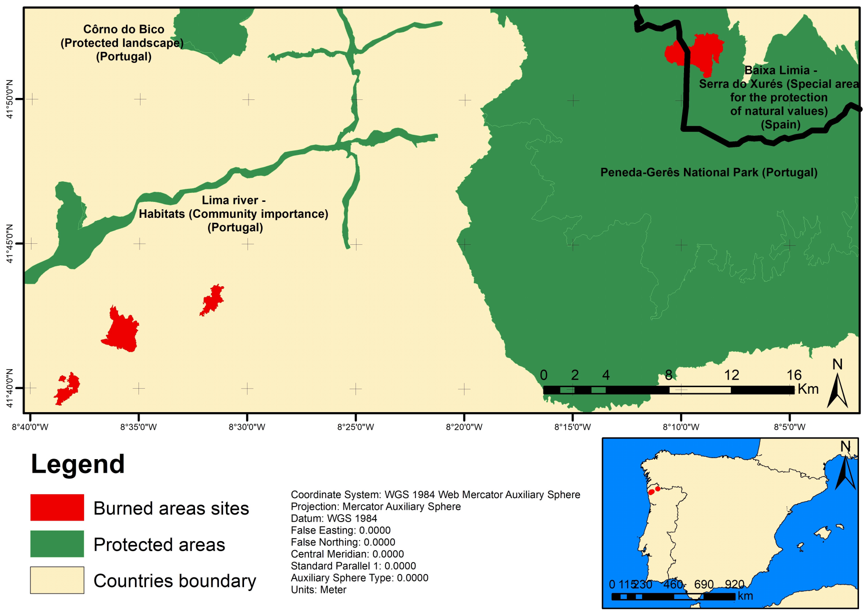

Figure 1. Study area. Source: Organized by the authors.

The areas cover 1294.8 hectares (ICNF, 2020), with one of the areas affecting the Peneda-Gerês National Park (PNPG), a protected area that together with the Spanish Natural Park of Baixa-Limia - Serra do Xurés, the Gerês-Xurés Transfrontier Park and the Biosphere reserve of the same name.

2.2. Data acquisition and processing

The research steps were adapted from the Kamusoko [13] and are available in the figure 2

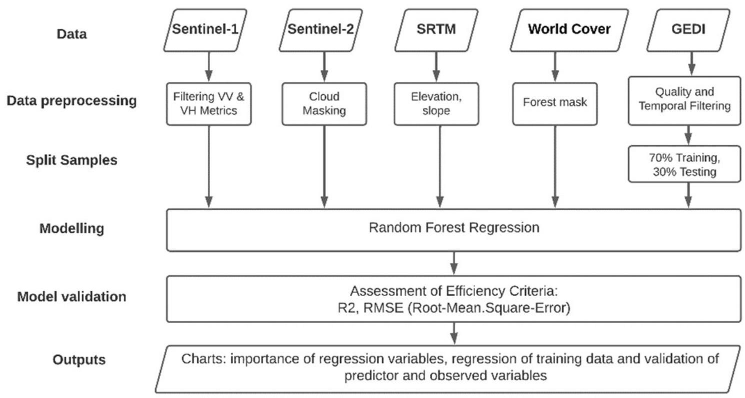

Figure 2. Workflow diagram depicting data preprocessing steps. Source: Organized by the authors.

Sentinel data for the period of September to December 2020 was used to model vegetation structure characteristics. The Sentinel-2 multispectral sensor data at level 2A (Surface Reflectance) was processed together with C-band Synthetic Aperture Radar (SAR) data from Sentinel-1 (Ground-Range-Detected). Both Sentinel datasets have a geometric resolution of 10 m which will be the target spatial resolution of the models [14]. Sentinel-1 data was filtered for single co-polarization of vertical transmission (VV) and dual-band cross-polarization in vertical transmission and horizontal re-acceptance (VH). For Sentinel-2 it was filtered for a percentage of nu-blurred pixels less than 20% and cloud masking.

Shuttle Radar Topography Mission (SRTM) [15] data was used to obtain elevation and slope values. This SRTM V3 product (SRTM Plus) is provided by NASA at a resolution of 1 arc-second (approximately 30m). The World Cover 2020 product of the European Space Agency (ESA) was used for the delimitation of the forest mask, this image has a 10m resolution based on Sentinel-1 and Sentinel-2 data.

We used the Global Ecosystem Dynamics Investigation (GEDI) level 2A data [11,16] for forest areas selection. GEDI data is stored as point geometries representing the centroid of the 25 m sample footprint. Vegetation structure attributes that were modelled are canopy height (98th percentile of the relative height metrics from GEDI L2A).

All data was processed in Google Earth Engine (GEE) using the Python API. The predictor variables for the model were determined from Sentinel-1, Sentinel-2, SRTM, and World Cover data. A machine learning approach was used, with the application of a Random Forest regression model. A random forest (RF) model is a machine learning ensemble technique that has proven its popularity in remote sensing applications due to its high accuracy and performance [14,17].

In total, about 10,000 quality-filtered GEDI samples were used for model training and validation of each vegetation structure attribute. The GEDI sample set was randomly split before modelling into a collection of training samples (70%) and test samples (30%) for model validation. The bands included in the classification were ['B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'B8', 'B11', 'B12', 'VV_iqr', 'VH_iqr', 'elevation', 'slope', 'Map']. The test samples, model-independent, are used to calculate several model efficiency criteria, such as the coefficient of determination (R^2) and root mean square error (RMSE).

3. Results and discussion

The importance of the variables used in the regression using Random Forest can be seen in the figure 3.

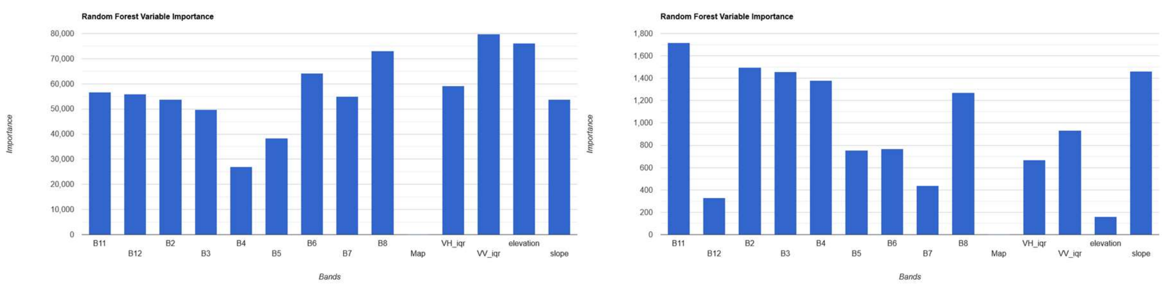

Figure 3. Importance of the variables before and after fires. Source: Organized by the authors.

B2 (blue) is the one that most contributes to the identification of burned areas [18], and B4 (red) was the one that underwent the greatest change, as it is the most sensitive to vegetation variations in the visible spectrum. Therefore, the lack or decrease in the amount of vegetation after fires results in a greater variation in its importance in the regression.

The wavelengths of the Red-edge range (B5, B6, B7) and B8 (NIR) are more sensitive in identifying the severity of fires. The bands of the Red-edge range can be used in the calculation of the NDVI705 (Difference Vegetation Red Edge Index) most suitable for forest monitoring and wildfires [19,20].

Sentinel's SWIR waveform is sensitive to changes in the structural crust, deformation of soil minerals, and soil salinity. These changes are identified in soil degradation processes resulting from wildfires that result in greater soil exposure [21]. Hence the greater variation in the importance of these variables in the regression. More details on soil degradation using hyperspectral data and remote sensing can be found at Goldshleger et al. [22].

The Sentinel-1 collects C-band synthetic aperture radar (SAR) imagery to provide VV and VH with dual-band cross-polarization and vertical transmit/horizontal receive data applied to forestry studies to identify fire scars. The results show that the VV polarization is more important than the VH, maintaining the same proportion before and after fires. Regarding terrain data, elevation is no longer an important variable in the post-fire regression and slope becomes one of the most important. This is because the slope becomes more easily identified in a digital elevation model (DEM) in an area with fewer trees. The slope values help to identify regions where the trees did not burn.

Concerning the height of the trees, in the results indicated before the fires the height varied from 5.21 to 20.16 meters and between 5.55 to 9.12 meters after the fires. The regression results of the training (70%) and validation (30%) dataset before the fires are shown in the figure 4.

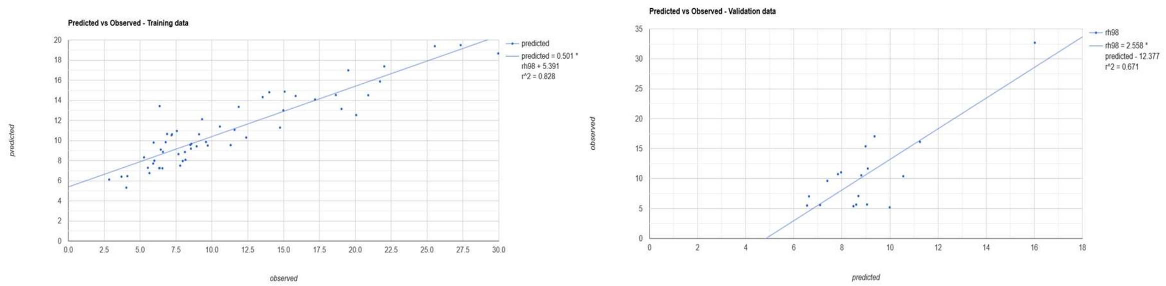

Figure 4. Prediction and observation are split into pre-fire training and validation data. Source: Organized by the authors.

In the training data set before the fires, a good result of r^2 0.82 and RMSE 3.47 was recorded, with a greater concentration of data close to the fit line and in the validation data set, r^2 0.67 and RMSE 5.23, with greater dispersion of the data to the surroundings of the model fit line.

After the fires, the training and validation data are shown in the figure 5.

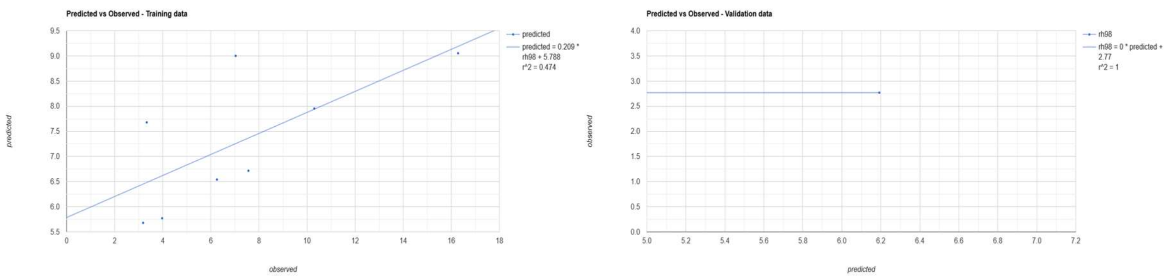

Figure 5. Prediction and observation are split into training and validation data after fires. Source: Organized by the authors.

Concerning the regression of the training data and observed after the fires, low values of r^2 are identified, in the training data the r^2 0.47 and RMSE 3.36 with large data dispersion and in the validation data the r^2 1 and RMSE 3.34, constituting bad statistical results. However, these results are acceptable in the context of a work that intends to measure the height of trees in burned areas before and after fires. The result is explained by the drastic reduction of trees for model validation after the fires, dramatically decreasing the number of predictor variable data (GEDI) needed for Random Forest regression.

4. Conclusions

The use of the GEE platform to analyze large amounts of data has shown potential in recent years, due to its flexibility in code construction and data crossing. In the present study, we sought to analyze the GEDI dataset, an important LIDAR instrument that since 2019 has provided data from planet Earth with great potential for analysis related to climate change, such as measuring carbon stock and vegetation structure.

We can conclude that the results presented in the present research are important and have great potential for application in the field of study of wildfires using remote sensing. It was possible to identify with relative precision the variations observed in the height of trees in burned areas in northern Portugal and Spain.

The regression results corroborate the decrease in tree height due to the occurrence of fires, demonstrating great potential for the application of the Random Forest model to predict tree height using LIDAR data and other predictor variables such as SAR and hyperspectral images from the Sentinel satellite.

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Conflicts of Interest: The authors declare no conflict of interest.

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