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Assessment of Sentinel-2 Spectral Features to Estimate Forest Height with the New GEDI Data

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Abstract. The unprecedented availability of vertical structure forest data provided by NASA Global Ecosystem Dynamics Investigation (GEDI), allows the validation of new methodologies based on other Remote Sensing (RS) sensors for monitoring forest parameters, such as Forest Height (FH). Previously, studies on FH estimation implied in-situ measurements or acquiring LiDAR data, which was limited and expensive. Opposing to the sampling nature of GEDI mission, Sentinel-2 optical products has a high revisiting frequency and a high spatial resolution favoring the implementation of forest monitoring methodologies. This work presents a study on the correlation and usability of linear and exponential regressions for estimating FH through Sentinel-2 imagery. It was also exploited the advantages of making estimations by study area, or by specific land cover types. Overall, a R^2 of 0.66 and a RMSE of 2.91m were achieved, and in case of specifying the vegetation type were 0.83 and 2.40m, respectively.

Keywords: GEDI, Sentinel-2, Remote Sensing, Forest Height, Parametric Regressions, LiDAR

1 Introduction

Forests ecosystems are the biggest carbon storages of the planet, playing an important role in its sustainability, preserving Earth climate [1], [2]. Forest management and monitoring are essential activities to assure the conservation of this ecosystems. Among the vertical structure parameters, Forest Height (FH) is a fundamental variable for describing forest areas. Furthermore, FH is commonly used for Aboveground Biomass (AGB) estimation [2], [3], which is an indicator of the forest fuel load. The information relatively to the fuel load is important for preparing wildfire management planning, by enabling an efficient scheduling of fuel treatments with the goal of reducing fire hazard. Besides controlling the forest fuel load, other proactive strategies, such as the implementation of fire and fuel breaks (FB) [4], rely on periodic treatments and monitoring their fuel load [5]–[7].

Some regions of the globe are strongly affected by wildfires, in particular the Mediterranean Europe (Portugal, Spain, France, Italy, and Greece) [8]. In Portugal, the Portuguese Institute for Nature Conservation and Forests (ICNF) implemented a Fuel Break Network (FBN), preventing wildfires and creating new opportunities for fire-fighting. FBs efficiency depends on the control of their fuel load [5]–[7].

The in-situ measurement of FH is not a suitable strategy for acquiring the periodic data needed for forest monitoring. The growing number of available Remote Sensing (RS) sensors lead to the development of new methodologies for estimating the FH. Although airborne platforms usually provide higher quality data, they do not have the time coverage to ensure the periodic availability of FH estimations, opposing to spaceborne platforms. Within the RS sensor types, Light Detection and Ranging (LiDAR) is the most suitable for estimating the FH [1], [3], [9]. However, LiDAR technologies are usually carried by aircrafts, having limited coverage and providing sparse measurements in time and space [1], [3], [9]. Adding to this, LiDAR data can be very expensive.

Spaceborne LiDAR was not optimized for vegetation analysis, until the recent NASA Global Ecosystem Dynamics Investigation (GEDI) dedicated to measuring the vertical structure of vegetation [1], [9]. Nevertheless, GEDI is just a sampling mission, not being suitable for regular monitoring. Other RS sensors, such as Optical and Synthetic Aperture Radar (SAR), have dedicated spaceborne platforms (Landsat, Sentinel-1, Sentinel-2), acquiring data with high revisiting frequency, being suitable for vegetation monitoring.

This article presents a study on how FH can be estimated, in a regular basis, from Remote Sensing Optical spectral features (SF, i.e., reflectance bands and spectral indices) for monitoring the FBs. A comparison between Sentinel-2 Level 2A products SF and the height above the ground (here used as FH) measurements from GEDI Level 2B products will be made, assessing which are the best SF to estimate the FH. As suggested in previous studies [9], ecological features influence the measured reflectance values, so beyond the overall analysis, local analysis will be performed. The study will also assess the proposed technique sensitivity to different forest types. The results will be assessed by the Root Mean Square Error (RMSE) and Coefficient of Determination (R^2) relatively to parametric regressions, and the Pearson's Correlation.

The article was written through five sections, with section 1 concerning Introduction and section 2 the relationship with Applied Artificial Intelligence (AI) Systems. In section 3 materials are presented (regions of interest, Remote Sensing data, and the used Spectral Indices); section 4 presents results, including which are the best achieved regressions overall, locally, and by land cover type; finally, in section 5 results are compared with previous studies, and conclusions are drawn.

2 Relationship with Applied Artificial Intelligence Systems

DoCEIS 2021 is dedicated to Technological Innovation for Applied AI Systems. This article proposes a feature selection pre-processing stage for FH estimation framework based on Artificial Intelligence methods (which will be a product of the PhD work where this article is framed). In this study, the best Remote Sensing SF for the estimation of FH in several Portuguese regions (within the FBN) with heterogenous ecological

features were selected. It was also studied the impact of estimating the FH locally and/or by land cover type. Summing up the question this manuscript proposes to answer which are the best SF to estimate the FH.

3 Materials and Methods

3.1 Study Areas

Four regions where fuel load treatments occurred during 2019 were selected within the Portuguese FBN. These treatments were detected using the methodologies presented in [5]–[7] and confirmed by ICNF. For each region, and to generate a more complete dataset, several samples from the treated areas and surrounding non-treated areas were select, providing low and high FH measurements. These regions are in different parts of the country, being subjected to different ecological conditions and land cover types (see **Error! Reference source not found.**, [10]).

3.2 Remote Sensing Data

For this study, data from GEDI and Sentinel-2 were used. GEDI is a LiDAR sensor onboard of the International Space Station, operating since April 2019 and optimized for forest monitoring. This mission has a global coverage between $\sim 51.6^\circ\text{N}$ and $\sim 51.6^\circ\text{S}$ latitudes and, according to [1], [9], it is expected to sample 4% of Earth's land surface. The GEDI Level-2B products provide Canopy Cover and Vertical Profile metrics (with a 25m spatial resolution), being the height above the ground, the metric used in this study as the FH (available in layer rh100). To guarantee the quality of data, only samples with the quality flags set (layers l2a_quality_flag and l2b_quality_flag) were used.

Sentinel-2 is the platform carrying the Multi-Spectral Instrument (MSI), an optical sensor from the Copernicus mission. The spatial resolution for the spectral bands is 10m for visible and Near Infrared (NIR) bands, 20m for red edge, Narrow NIR, and Short Wave Infrared (SWIR) bands, and 60m for coastal aerosol, cirrus, and water

Table 1. Description of the Regions of Interest.

Region of Interest – County	Relative Location in Country	Land Cover Type
Amieira – Gavião	Inland South Center	Eucalyptus and Cork tree forests
Besteiros – Portalegre	Inland South Center	Eucalyptus, Pine, and Cork tree forests
Capinha – Fundão	Inland North Center	Eucalyptus forests
Famalicão – Guarda	Inland North Center	Pine forests

vapor bands [5]. This mission is composed by two satellites allowing this constellation to achieve a 5-days revisiting period. Sentinel-2 Level-2A products available in Copernicus Open Access Hub were used. Level-2A category corresponds to Bottom-of-Atmosphere products, being the atmospheric corrections performed by Sen2Cor algorithm [11]. Although several reflectance bands have the spatial resolution of 10m, due to the spatial resolution of 25m from GEDI, the Sentinel-2 20m resolution bands and the visible spectrum bands resampled to 20m were used. For the NIR band, instead of using B08 (NIR) resampled to 20m, B8A (NIR – narrow band) was used.

The study period was March 2020 to September 2020, having been selected 100 samples (25 per region) from GEDI. For each sample date, the closest corresponding Sentinel-2 observation, was used. From this dataset, 50 samples were from Eucalyptus Forests, 33 from Pine Forests, and 17 from Cork Tree Forests.

3.3 Methods

In Remote Sensing is common to use derivatives from reflectance measurements, such as spectral indices. The selected indices for the analyses are presented in Table 2. Equations (1), (2), (3), (4), (5) correspond to normalized spectral differences [1], [6], [7]. Equations (1) and (2) are the Normalized Difference Vegetation Index (NDVI), using the Red and NIR band, respectively; (3) and (4) are the Normalized Difference Moisture Index (NDMI), using the respective SWIR bands; and NDSWIR, which is the Normalized Difference between SWIR bands. The other indices are optimized for the vegetation: Enhanced Vegetation Index (EVI) and Modified Soil-Adjusted Vegetation Index 2 (comparing this with MSAVI1, it has the advantage of not using the L parameter).

The goal for this study is to define which are the best Remote Sensing SF for FH estimation by comparison with GEDI data. The full dataset is used for the analysis, being grouped by land cover, region of interest, and by both criteria. Firstly, the Pearson's correlation with the FH is computed for all selected features. The features more

Table 2. Spectral Indices used in this study.

Spectral Index	Equation
$NDVI_{664nm} = (B8A - B04) / (B8A + B04)$	(1)
$NDVI_{559nm} = (B8A - B03) / (B8A + B03)$	(2)
$NDMI_{1610nm} = (B8A - B11) / (B8A + B11)$	(3)
$NDMI_{2200nm} = (B8A - B12) / (B8A + B12)$	(4)
$NDSWIR = (B11 - B12) / (B11 + B12)$	(5)
$EVI = 2.5 * ((B8A - B04) / (B8A + 6 * B04 - 7.5 * B02 + 1))$	(6)
$MSAVI2 = (2 * B8A + 1 - \sqrt{(2 * B8A + 1)^2 - 8 * (B8A - B04)}) / 2$	(7)

correlated with the FH were selected for further analysis. Next, two parametric regressions (Linear – $a \cdot x + b$; Exponential – $a \cdot \exp(b \cdot x)$) were tested, being evaluated by the R^2 , indicating which is the best regression. Finally, the RMSE is computed being assessed the uncertainty of the estimation.

The results will be obtained by group (land cover and region of interest) and overall considering all cases. This strategy will show the advantages of grouping the data.

4 Discussion and Results

The detailed results are presented in Fig. 1, Fig. 2, and Fig. 3. It is shown the Pearson's Correlation between the SF and FH and the other figures show the R^2 for linear and exponential regressions using those variables. It is used a color scale, Green to Red, being the greener values the best results.

The results from the Pearson's correlation are presented Fig. 1. From the overall results correlations above the 0.75 were achieved, which shows that there is in fact a relation between the SF and GEDI's FH. The bands exhibit a better correlation than the indices, being bands 3, 4 and 5 the ones with higher correlation. Within the indices, NDVI_{664nm} and MSAVI2 are the most suitable.

Grouping data by region of interest led to better results than grouping by land cover type (Fig. 1). Relatively to land cover type the best class was the Eucalyptus Forest (0.91 for NDVI_{2200nm}) and the worst was Pine Forest class (0.67 for B03). When grouping by region of interest, Capinha was the best region achieving 0.96 (note that in this region there were only Eucalyptus Forest) for both NDVIs, and the worst region was Fama-lição with correlation of 0.69 for B03. With this criterion, with exception of Capinha, spectral bands exhibit again a better correlation with FH.

The highest correlations were achieved for data grouped by region of interest and land cover type, being Besteiros the best example (that has the three land cover types dealt in this study) achieving an overall correlation of 0.81 for B12, and when divided by forest type it has achieved 0.93 for B11 in Eucalyptus; 0.84 for B12 in Pine; and 0.97 for B05 in Cork trees.

The R^2 values for each regression and all defined groups are presented in Fig. 2 and Fig. 3. The comparison of the overall values shows that the exponential regression has the best estimation. It achieves a R^2 of 0.67 for B05, opposing to 0.63 for B03 in the linear regression. Again, the best spectral features when analyzing the overall data are spectral bands. Inspecting all the proposed approaches, most estimations were better when using the exponential regression. As expected, relatively to the grouping criterion, the same conclusions are reached, being the highest R^2 obtained, 0.96, for the exponential regression for Besteiros Cork tree with the B05. The best SF and regression for each group is presented in Table 3. The uncertainty of FH estimations was assessed by the RMSE, being presented in Table 3 the results for the best regressions defined before. To understand the impact of the RMSE value, it is also presented the range of FH measurements and FH mean for each regression. The average RMSE of all regressions is 2.33m and there are not values greater than 4.00m. Since FH values range between 3m and 22m, it shows that spectral features are suitable for measuring FH according to GEDI data.

5 Conclusions and Future Work

GEDI measurements offer a new opportunity to define new methodologies for forest monitoring. This article presented an exploratory study about the relation between SF and the FH measurements from GEDI. It was verified that a relation exists and may be used for predicting this parameter. A comparison between the RMSE achieved by this study and [3], shown that the values were similar, although here they were applied for smaller areas, and there were used less samples. As in [9], where the local calibration was exploited with good results, this work verified the same. Beyond that, this study shown that joining the local information to the land cover will further improve results. Although increasing the information about the region, where the estimation is being applied, leads to less generic methods, being applicable to smaller areas. The best approach may be to use the regression considering only the land cover, which already improves the estimation, and it still is a generic approach to the problem. It was also shown that different land covers have different results. Eucalyptus forest achieved the best results, probably due its dense occupation of the soil, being more robust to the impact of other terrain characteristics in the reflectance measurements, opposing to Pine forest that usually are not as well behaved as the previous. Finally, the fact that the relation is not strictly linear was expected because the spectral features are not sensible only to FH, but also to the AGB, and other forest parameters.

In continuation of this work, non-parametric regressions will be applied to understand if there is an improvement on the estimation. The generation of larger datasets and

Table 3. Regression (R) method (E- Exponential; L – Linear) by group and respective uncertainty.

Group	R	SF	RMSE (m)	FH Range (m)	FH Mean	Nº of Samples
Eucalyptus	E	B12	2.40	[3.28;21.14]	9.22	50
Pine	L	B05	3.68	[4.65;21.86]	10.32	33
Cork tree	L	B11	1.71	[4.26;16.47]	8.91	17
Amieira	L	B11	1.76	[3.28;15.38]	7.26	25
Besteiros	L	B12	2.40	[5.07;20.40]	9.96	25
Capinha	E	NDVI _{559nm}	2.44	[3.66;21.14]	10.77	25
Famalicão	E	B03	3.97	[4.65;21.86]	10.13	25
Amieira – Eucalyptus	E	NDMI _{2200nm}	1.33	[3.28;15.38]	6.64	15
Amieira – Cork Tree	L	B11	2.07	[4.26;13.14]	8.18	10
Besteiros – Eucalyptus	E	NDMI _{1610nm}	2.33	[5.07;20.40]	9.20	10
Besteiros – Pine	L	B12	1.45	[7.51;13.89]	10.77	8
Besteiros – Cork Tree	E	B05	0.71	[7.17;13.81]	9.95	7
Capinha – Eucalyptus	E	NDVI _{559nm}	2.44	[3.66;21.14]	10.77	25
Famalicão – Pines	E	B03	3.97	[4.65;21.86]	10.12	25
Overall	E	B05	2.91	[3.28;21.86]	9.53	100

considering new land covers. Also, the definition of a FH estimation methodology with resource to optical Remote Sensing data.

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Region of Interest	Land Cover	Spectral Features														
		B02	B03	B04	B05	B06	B8A	B11	B12	NDVI 664	NDVI 559	NDMI 1610	NDMI 2200	NDSWIR	EVI	MSAVI2
	Eucalyptus	0.85	0.87	0.87	0.85	0.66	0.48	0.85	0.89	0.87	0.84	0.89	0.91	0.83	0.79	0.86
	Pine	0.53	0.67	0.66	0.66	0.39	0.37	0.51	0.50	0.58	0.53	0.32	0.35	0.39	0.34	0.57
	Corktree	0.52	0.61	0.61	0.70	0.58	0.57	0.81	0.72	0.48	0.41	0.61	0.57	0.39	0.16	0.46
Amieira		0.80	0.82	0.83	0.83	0.74	0.73	0.88	0.86	0.80	0.76	0.81	0.78	0.56	0.74	0.80
Besteiros		0.77	0.81	0.76	0.77	0.52	0.47	0.81	0.81	0.70	0.77	0.70	0.71	0.54	0.45	0.71
Capinha		0.93	0.92	0.92	0.89	0.68	0.26	0.88	0.92	0.96	0.96	0.90	0.94	0.88	0.92	0.94
Famalicão		0.52	0.69	0.65	0.65	0.43	0.40	0.53	0.49	0.58	0.55	0.31	0.34	0.37	0.33	0.57
Amieira	Eucalyptus	0.92	0.92	0.92	0.91	0.77	0.73	0.94	0.94	0.95	0.94	0.96	0.95	0.93	0.94	0.94
	Corktree	0.10	0.28	0.21	0.38	0.57	0.69	0.70	0.44	0.09	0.02	0.36	0.06	0.28	0.46	0.10
Besteiros	Eucalyptus	0.91	0.93	0.86	0.90	0.69	0.57	0.93	0.92	0.82	0.89	0.92	0.90	0.61	0.54	0.81
	Pine	0.82	0.80	0.77	0.68	0.16	0.01	0.82	0.84	0.67	0.67	0.72	0.74	0.69	0.51	0.69
Capinha	Corktree	0.89	0.94	0.89	0.97	0.74	0.65	0.94	0.92	0.78	0.70	0.78	0.80	0.84	0.39	0.78
	Eucalyptus	0.93	0.92	0.92	0.89	0.68	0.26	0.88	0.92	0.96	0.96	0.90	0.94	0.88	0.92	0.94
Famalicão	Pine	0.52	0.69	0.65	0.65	0.43	0.40	0.53	0.49	0.58	0.55	0.31	0.34	0.37	0.33	0.57
Overall		0.72	0.79	0.78	0.78	0.56	0.46	0.75	0.76	0.76	0.73	0.69	0.71	0.66	0.60	0.75

Fig. 1. Absolute values of Pearson's correlation, in bold the best values by group. Scale Green-white-red for best values by group.

Region of Interest	Land Cover	Spectral Features														EVI	MSAVI2
		B02	B03	B04	B05	B06	B8A	B11	B12	NDVI 664	NDVI 559	NDMI 1610	NDMI 2200	NDSWIR			
	Eucalyptus	0.72	0.75	0.76	0.72	0.44	0.23	0.73	0.79	0.76	0.70	0.79	0.83	0.68	0.63	0.74	
	Pine	0.28	0.44	0.43	0.43	0.15	0.14	0.26	0.25	0.33	0.28	0.10	0.12	0.15	0.11	0.33	
	Corktree	0.27	0.38	0.37	0.49	0.34	0.33	0.65	0.51	0.23	0.17	0.38	0.33	0.16	0.03	0.21	
Amieira		0.64	0.67	0.68	0.69	0.54	0.53	0.78	0.74	0.64	0.58	0.65	0.60	0.31	0.55	0.64	
Besteiros		0.59	0.65	0.58	0.59	0.27	0.22	0.65	0.66	0.49	0.59	0.50	0.50	0.29	0.21	0.51	
Capinha		0.86	0.85	0.84	0.79	0.46	0.07	0.77	0.85	0.92	0.92	0.82	0.88	0.77	0.85	0.89	
Famalicão		0.27	0.48	0.42	0.42	0.19	0.16	0.28	0.24	0.34	0.30	0.10	0.12	0.14	0.11	0.32	
Amieira	Eucalyptus	0.85	0.84	0.85	0.82	0.59	0.53	0.89	0.89	0.90	0.89	0.92	0.91	0.87	0.89	0.89	
Besteiros	Corktree	0.01	0.08	0.04	0.14	0.33	0.47	0.49	0.19	0.01	0.00	0.13	0.00	0.08	0.21	0.01	
	Eucalyptus	0.83	0.86	0.74	0.80	0.48	0.33	0.87	0.85	0.68	0.80	0.85	0.81	0.37	0.30	0.65	
	Pine	0.67	0.64	0.59	0.46	0.03	0.00	0.68	0.70	0.45	0.45	0.52	0.55	0.47	0.26	0.47	
	Corktree	0.79	0.89	0.79	0.95	0.55	0.43	0.89	0.84	0.60	0.49	0.61	0.64	0.70	0.15	0.60	
Capinha	Eucalyptus	0.86	0.85	0.84	0.79	0.46	0.07	0.77	0.85	0.92	0.92	0.82	0.88	0.77	0.85	0.89	
Famalicão	Pine	0.27	0.48	0.42	0.42	0.19	0.16	0.28	0.24	0.34	0.30	0.10	0.12	0.14	0.11	0.32	
Overall		0.52	0.63	0.61	0.61	0.32	0.21	0.56	0.58	0.58	0.54	0.48	0.51	0.44	0.37	0.56	

Fig. 2. R² values for linear regression.

Region of Interest	Land Cover	Spectral Features														EVI	MSAVI2
		B02	B03	B04	B05	B06	B8A	B11	B12	NDVI 664	NDVI 559	NDMI 1610	NDMI 2200	NDSWIR			
	Eucalyptus	0.72	0.77	0.79	0.76	0.49	0.24	0.78	0.83	0.77	0.72	0.76	0.81	0.69	0.66	0.78	
	Pine	0.28	0.48	0.50	0.50	0.16	0.15	0.29	0.27	0.34	0.26	0.09	0.11	0.14	0.10	0.34	
	Corktree	0.30	0.40	0.40	0.50	0.37	0.38	0.63	0.52	0.25	0.18	0.38	0.34	0.19	0.03	0.23	
Amieira		0.63	0.66	0.69	0.70	0.55	0.58	0.76	0.72	0.62	0.56	0.62	0.59	0.40	0.56	0.64	
Besteiros		0.60	0.67	0.57	0.59	0.27	0.23	0.63	0.65	0.46	0.58	0.45	0.47	0.28	0.18	0.49	
Capinha		0.92	0.91	0.90	0.86	0.52	0.08	0.82	0.87	0.91	0.93	0.79	0.85	0.77	0.86	0.92	
Famalicão		0.28	0.55	0.53	0.52	0.21	0.18	0.35	0.29	0.36	0.29	0.09	0.11	0.13	0.09	0.35	
Amieira	Eucalyptus	0.88	0.87	0.88	0.87	0.65	0.60	0.91	0.92	0.92	0.90	0.94	0.95	0.91	0.95	0.91	
	Corktree	0.01	0.07	0.04	0.13	0.31	0.45	0.44	0.19	0.01	0.00	0.15	0.01	0.09	0.18	0.01	
Besteiros	Eucalyptus	0.85	0.87	0.76	0.74	0.48	0.34	0.85	0.89	0.72	0.88	0.94	0.92	0.45	0.27	0.71	
	Pine	0.67	0.61	0.56	0.42	0.02	0.00	0.65	0.68	0.43	0.44	0.48	0.52	0.44	0.25	0.46	
	Corktree	0.81	0.93	0.83	0.96	0.59	0.48	0.91	0.89	0.60	0.47	0.61	0.66	0.72	0.14	0.60	
Capinha	Eucalyptus	0.92	0.91	0.90	0.86	0.52	0.08	0.82	0.87	0.91	0.93	0.79	0.85	0.77	0.86	0.92	
Famalicão	Pine	0.28	0.55	0.53	0.52	0.21	0.18	0.35	0.29	0.36	0.29	0.09	0.11	0.13	0.09	0.35	
Overall		0.54	0.66	0.66	0.67	0.35	0.22	0.60	0.61	0.59	0.54	0.46	0.49	0.44	0.33	0.59	

Fig. 3. R² values for exponential regression.