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# *Eucalyptus* Leaf area index estimation from Sentinel 2 images: importance of genotype and sun and view acquisition geometry

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***ABSTRACT:*** *Brazil is a major producer of wood, with Eucalyptus plantations covering over 7 million hectares. Leaf area index (LAI) is a crucial parameter for determining stand carbon and water balance, and ultimately assessing the crop growth status. However, LAI is highly variable in space, within and between stands, and temporally, across rotations. This study aims to investigate the relationship between LAI and various vegetation indices derived from Sentinel 2 images, and develop empirical equations calibrated at the Eucflux site with Root Mean Squared Error values as low as* 0.49 $m^2/m^2$. *The incorporation of variables related to satellite and sun acquisition geometry significantly improves the accuracy of the prediction model. In addition, separating the model by genotypes greatly improves its performance, but may affect transferability.*

*Keywords: LAI, Sentinel-2, genotypes, sun-sensor geometry, Eucalyptus*

## Introduction

The availability of spatiotemporal earth observation data broadens the scope of analysis of forest plantation traits, such as leaf area index (LAI). LAI is a dimensionless structural canopy trait referring to the surface of green leaf area per unit of ground area. Many surface processes depend heavily on LAI, which can be used in multiple applications such as yield forecasting and disturbance monitoring (Yin *et al.*, 2019).

Empirical models are commonly used to estimate biophysical traits using remote sensing data, which explore the correlation between canopy traits and vegetation indices (VIs). VIs are spectral band combinations that enhance spectral features sensitive to vegetation (Bannari *et al.*, 1995). Although these models lack generic capacity, they continue to be used, especially for local and crop-specific applications (Bajocco *et al.*, 2022)

Vegetation canopy reflectance is related to LAI, but is also a function of vegetation traits, such as leaf inclination, chlorophyll content etc which varies by species/genotypes. Additionally, the sun-view geometry at image acquisition may also strongly influence the reflectance response. Recent research has shown that geometry variables can explain 30% to 43% of the spectral variability of Sentinel-2 bands, indicating that taking into account biophysical information and geometry variables can significantly improve LAI estimations (Kganyago *et al.*, 2023)

The study aims to screen the potential of vegetation indices (VIs) derived from Sentinel-2 (S2) imagery to estimate LAI in eucalyptus plantations in a study site in São Paulo, Brazil. The study's specific objective is to determine if incorporating geometry and genotype variables improves the fitting of models to the data.

**Material and methods**

*Area of interest (AOI)*

The study area is a 200-hectare commercial eucalyptus plantation located in Itatinga, São Paulo, Brazil, and is part of the Eucflux project. The plantation consists of 25 genotypes planted in five blocks for the current rotation (2019-onwards), as well as four other blocks of 16 genotypes conducted as coppice. Other four plots were measured around a flux-tower on the main genotype of the whole Eucflux stand. Only the coppice blocks were not used in this study. The site configuration is explained in detail in a previous study by (Le Maire *et al.*, 2019)

*Data*

The data consists of *in-situ* LAI measurements and remote sensing data. LAI measurements were obtained through destructive sampling, as explained in (Le Maire *et al.*, 2011), between April 2019 and December 2021. The remote sensing data consists of S2 surface reflectance data (level-2A). To minimize plot border effects, the pixels were extracted using an inner spatial buffer of 10 meters for each plot. A surface-weighted average of the reflectances were computed giving more weight to pixels that covers a larger area within the plot. The S2 data falls within a window of +/-10 days around the LAI *in-situ* measurement date.

*Experimental setup*

The selection of vegetation indices (VIs) was based on literature review and careful consideration of the following criteria: 1) the Normalized Difference Family of Indices, with a particular emphasis on the widely used NDVI that uses near-infrared and red bands, as well as other indices that incorporate the red-edge, green, and blue bands that have been shown to enhance the estimation of Leaf Area Index LAI (Wang et al., 2007); 2) indices containing short-wave infrared (SWIR) bands; and 3) additional indices specifically designed to correlate with traits that could covariate with LAI, such as canopy water or chlorophyll content. The shortlisted VIs are presented in Table 1.

Three types of regression models were evaluated for each vegetation index: a base model that relates LAI to the VI, a second model accounting also for geometry variables (SZA, VZA, RAA), and a third model a model that builds on the second but calibrated separately for each genotype. The models were trained on 80% of the data using 10-fold cross-validation. All variables used in the models were normalized before training.

The models were evaluated based on two metrics: Akaike information criterion (AIC) and prediction root mean square error (RMSE). AIC was used to identify the model that explains the greatest amount of variation using the fewest variables. The model with the lowest AIC and above 2 AIC units lower than the model being compared with is considered to be better. RMSE measures the difference between the predicted values and actual observations in the same units as the observations. The remaining 20% of the dataset, sample across all years, were used for testing the model.

**Table 1 -** Vegetation indices from Sentinel-2 MSI data.

| Index | Name | S2 Equation | Reference |
|---|---|---|---|
| CIRE | Chlorophyll Index Red Edge | (B8 / B5) - 1 | (Gitelson et al., 2003) |
| GBNDVI | Green-Blue Normalized Difference Vegetation Inde | (B8 – (B3 + B2)) / (B8 + (B3 + B2)) | (Wang et al., 2007) |
| MCARI70: | Modified Chlorophyll Absorption in Reflectance Index | ((B6 – B5) - 0.2) * (B6 – B3)) * (B6/ B5) | (Wu et al., 2008) |
| MNDVI | Modified Normalized Difference Vegetation Index | (B8 – B12) / (B8 + B12) | (Jurgens, 1997) |
| NDCI | Normalized Difference chlorophyll Index | (B5 – B4) / (B5 + B4) | (Mishra; Mishra, 2012) |
| NDWI1 | Normalized Difference Water Index | (B8A – B11) / (B8A + B11) | (Gao, 1996) |
| NDVI | Normalized Difference Vegetation Index | (B8– B4) / (B8+ B4) | (Rouse et al., 1974) |
| NDVI705 | Normalized Difference Vegetation Index 705 | (B6– B5) / (B6+ B5) | (Gitelson; Merzlyak, 1994) |
| SeLI | Sentinel-2 LAI Green Index | (B8A – B5) / (B8A + B5) | (Pasqualotto et al., 2019) |

## Results and discussion

The AIC estimated for each VI's model is displayed in Figure 2, sorted according to the lowest AIC (Figure 1). The VI which gave the best result among all models was GBNDVI, under the genotype configuration, with an RMSE of 0.49 $m^2/m^2$.

All regression models showed significant improvement when geometry variables were incorporated (AIC > 2). As illustrated by (Kganyago *et al.*, 2023) the rate of spectral variability explained by geometric variables varies by band. Since VIs are computed from bands compositions that might be differently affected by sun-sensor geometry, some VIs might be more sensitive to these variables than others. The NDCI was the VI most affected by the incorporation of geometry variables. Its inclusion reduced the AIC by approximately half and decreased the RMSE by around 11%. The lowest error under the geometry model configuration (not considering genotype) was obtained with CIRE, with an RMSE of 0.63 $m^2/m^2$ (Figure 1).

In regard to the third type of regression model, most models strongly benefit from considering the genotype (1 to 25) as explanatory variables. Concerning the RMSE, the improvements between the base models and the genotype models ranged from 3% to 11%. The GBNDVI geometry + genotype model obtained the lowest RMSE (0.49 $m^2/m^2$) (Figure 1).

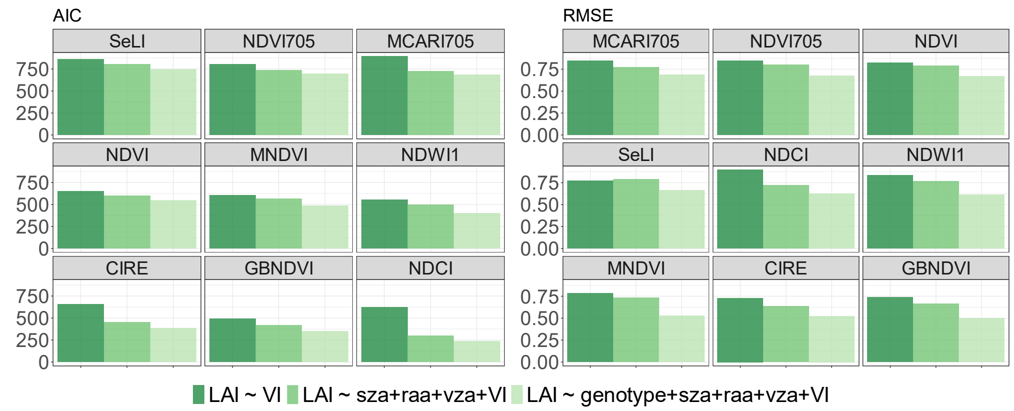


**Figure 5** – AIC (left) and RMSE (right) sorted by VI and model type.

These improvements in LAI predictions are likely due to distinct characteristics of eucalyptus genotypes, such as leaf angle distribution, chlorophyll and water content, and other factors that affect canopy reflectance. A genotype-aware model reduces error but is difficult to transfer to other sites. An alternative approach is to use physical models to understand how individual traits influence reflectance behavior, which can help in predicting LAI values. Figure 2 shows measured and predicted LAI values obtained from the genotype-aware model. Notice that LAI considerably varies among genotypes.

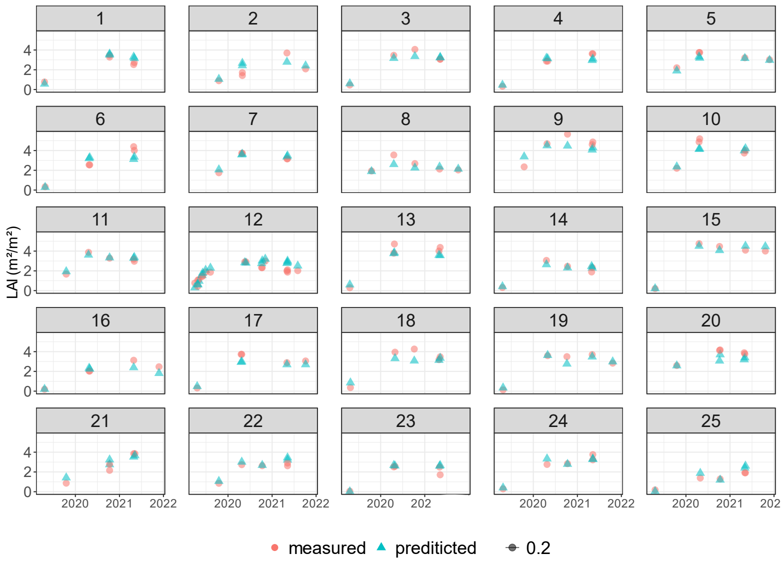


**Figure 6** – Predicted LAI (blue triangles) and measured LAI (orange dots) from 2019 to 2021 on the test dataset per genotype (1 – 25).

## Conclusion

The key conclusions are 1) all VIs benefit from adding sun-view geometry to predict LAI and 2) including the genotypes as explanatory variables reduce the error by up to 11% but at the expense of genericity loss.

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