# Towards the Improvement of Forest Leaf Area Index Assessed from Sentinel-2 Imagery by Integrating LiDAR Information

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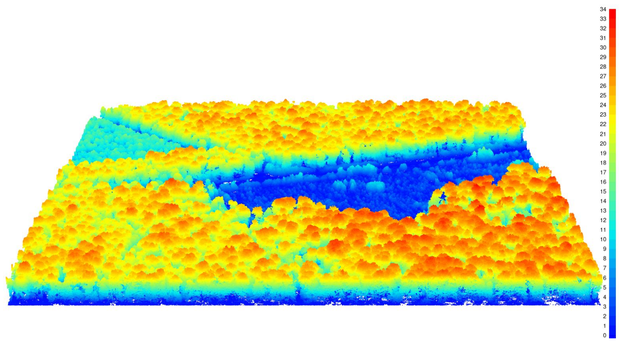
## INTRODUCTION

**Context:** Monitoring Leaf Area Index (LAI) dynamics is key for multiple ecosystem functions (microclimate, forest health, fire risk mitigation). For example, refined modeling of the links between microclimate and canopy properties, including LAI, is needed to identify more resilient forest management practices addressing challenges raised by climate change. However, current techniques for remotely sensed LAI monitoring show limitations when using individual sensors.

**Objectives:** 1. Identify the structural factors influencing the accuracy of the LAI estimation obtained from Sentinel-2 data processed with physical modeling.
2. Enhance LAI assessment by combining Sentinel-2 and LiDAR information.

## MATERIALS

**Study Site:** Mormal French State Forest (Deciduous Forest)



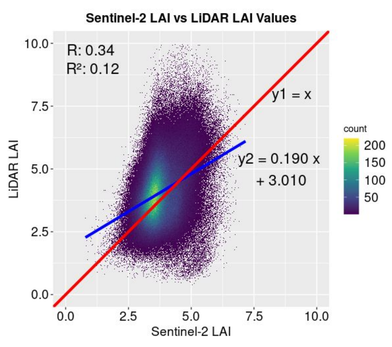
**ALS:** 3D point clouds (25 to 50 pts/m²) acquired with leaf-on conditions (June 16 and July 19, 2021)

**Sentinel-2:** Multispectral image (June 14, 2021)

## METHODS

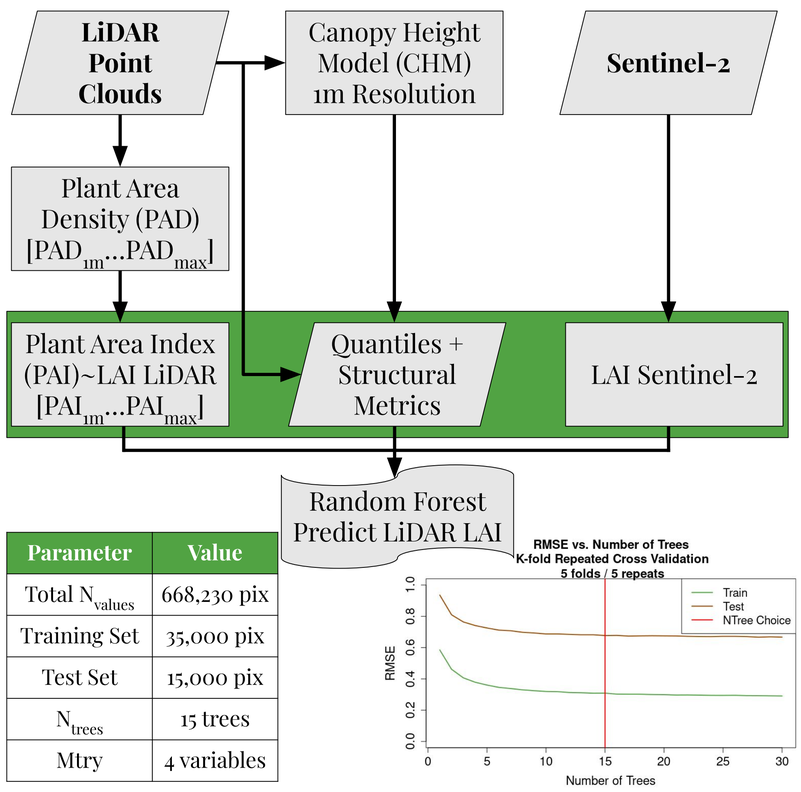
**Initial Comparison:**

1. The correlation between LAI values derived from Sentinel-2 and LiDAR is positive but low (R=0.34).
2. LAI assessment capacity from these two individual sensors is highly limited in forest ecosystems.




**Hypotheses:**

1. LiDAR data provide the most accurate LAI estimation.
2. Both canopy depth and heterogeneity influence LAI assessed from PROSAIL [3] inversion applied to Sentinel-2:
   - Sentinel-2 reflectance is insensitive to an increase in LAI above a certain threshold (~5 m²/m²): only the uppermost vegetation layer drives LAI assessment.
   - The turbid medium assumption of PROSAIL is limiting when assessing vegetation properties from a heterogeneous canopy.




| Parameter | Value |
|---|---|
| Total $N_{values}$ | 668,230 pix |
| Training Set | 35,000 pix |
| Test Set | 15,000 pix |
| $N_{trees}$ | 15 trees |
| Mtry | 4 variables |

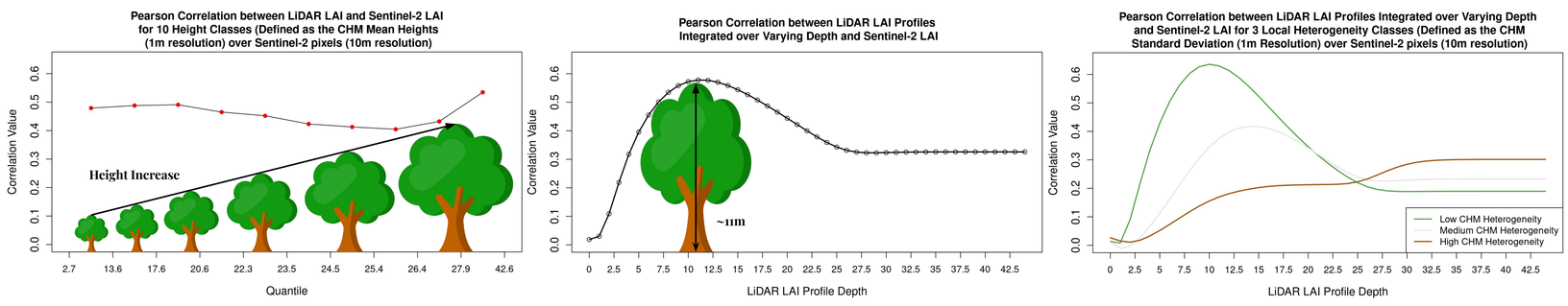
**Inter-Comparison Framework:**

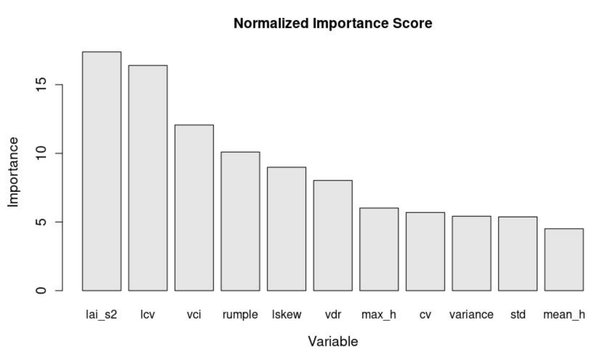
1. LAI Estimations (10m x 10m pixel grids):
   - LiDAR: Gap fraction method [1-2].
   - Sentinel-2: PROSAIL hybrid inversion [3-4].
2. Definition of 10 height classes and 3 heterogeneity classes using quantiles of mean and standard deviation of CHM heights within a Sentinel-2 pixel.
3. Correlation between LAIs analyzed by height class, heterogeneity class, and canopy depth.
4. Parametrization, train and test of a random forest regression model [5] to obtain a LiDAR-like LAI based on Sentinel-2 LAI combined with canopy height and heterogeneity structural metrics.
5. Determination of the variable importance for the estimation of LiDAR-like LAI.

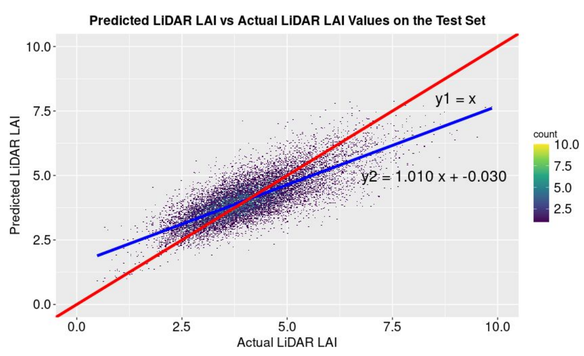
**Structural Metrics:**

1. *CHM-related:* [mean, max, standard deviation (std), coefficient of variation (cv), variance, L-moments [6] ($L_{cv}$, $L_{skew}$) of the height distribution.
2. *Point Clouds-related:* Vertical Distribution Ratio (VDR [7]), Vertical Complexity Index (VCI [8]), rumple index.

## RESULTS AND DISCUSSIONS




| Metric (Actual LiDAR LAI vs Predicted LiDAR LAI on the Test Set) | Value |
|---|---|
| R | 0.78 |
| $R^2$ | 0.61 |
| RMSE | 0.67 |
| Bias | 0.002 |
| MAE | 0.52 |

1. Using **height classes** improves the LAIs correlation overall, with marginal variations in correlation between classes (R=0.48 ± 0.05).
2. The thickness of the vegetation layer used to integrate LAI from LiDAR PAD profiles **significantly impacts** the correlation. This **validates our hypothesis that S2 signal is mostly determined by the upper vegetation layer** ($R_{max}$ at 11 meters depth).
3. The LAIs correlation **is stronger** when selecting pixels with low CHM heterogeneity, **confirming our hypothesis related to vegetation heterogeneity**.
4. The most important variables are **S2 LAI, $L_{cv}$, and VCI**. Sentinel-2 LAI is inaccurate when used as unique predictor, but strongly contributes to accurate LiDAR LAI prediction. $L_{cv}$ and VCI **are significant descriptors of canopy heterogeneity**.
5. Our model **strongly improves the estimation of LiDAR LAI** (R=0.78, $R^2$= 0.61).
6. **Next steps** include application at full site scale, training sampling accounting for spatial correlation, and generalization analysis in space and time [9].

**References**

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