SENSAGRI Leaf Area Index product

The SENSAGRI Leaf Area Index (LAI) product is derived from **Sentinel-2** (**S2**) images and provides LAI over photosynthetic functioning ***green*** **vegetation** (**LAI Green**) and over senescent ***brown*** **vegetation** (LAI Brown). While the mapping of LAI Green is well established that is less the case for LAI Brown. When crop senescence, leaves remain on the plant until falling off or being harvested. This senescent vegetation represents a significant amount of aboveground biomass and are a key factor in the carbon cycle (Vuichard *et al*., 2007). Spatially-explicit quantification of LAI Brown can thus help monitoring crop damage before harvesting due to drought or other natural hazards. Also, senescent fields are more fire-prone than green fields, reason why monitoring LAI Brown can contribute to fire risk assessments (Delegido *et al*., 2015).

The retrieval algorithm is based on **Gaussian Processes Regression** (**GPR**) technique, as a MLRA (*Machine Learning Regression Algorithm*) able to capture nonlinear relationships of remote sensing image features without assuming an explicit prior data distribution. In GPR, the model is adjusted to predict a variable of interest using training datasets of input– output data pairs. Particularly, the input refers to S2 reflectance spectra and the output is the LAI biophysical parameter. In general, the GPR model establishes an input-output relation between the new input spectrum and all the spectra used in the training phase. The prediction is obtained by (1) quantifying the similarity between training and prediction spectra using an optimized kernel function and (2) linearly combining these values according to specific weights. All kernel's hyperparameters are usually learned by maximizing the marginal likelihood over the training set. In essence, the prediction for a new input spectrum in GPR is a normal distribution, whose mean value represents the most likely value of the parameter modeled during the training. Each predicted mean value comes with an associated predictive variance, which provides a description of the estimate confidence interval. Finally, GPR allows evaluating the relative contribution of each single band to the model, as ranking of the relevant features (bands) from the spectral input data is obtained (Camps-Valls *et al*., 2011). See Rasmussen & Williams (2006) for further details and GPR formulation description.

Two independent GPR models were trained for estimating LAI Green and LAI Brown. The data used to adjust the models came from ground LAI data, measured over green or senescent fields, respectively, and their corresponding S2 reflectance observations. Only S2 10 and 20 m spatial resolution bands were used, i.e. 10 spectral bands in total. Both models were implemented in an automated processing chain which admits as input S2 images (S2 Tile) and provides a 20 m spatial resolution LAI product. According to the training spectral configuration, 10 bands are imported at 20m pixel size. Additionally, S2 scene classification band is also used as mask to exclude cloud and water pixels from the retrieval scheme. The retrieval process is image-based, providing pixel-wise LAI estimates (μ [m^2/m^2]), LAI associated uncertainty (*Standard Deviation* (SD) [m^2/m^2]) and LAI relative uncertainty (*Coefficient of Variation* (CV) [%]), independently por LAI Green and for LAI Brown. In addition, the LAI product includes a LAI Total, which merges both LAI Green and LAI Brown estimates, so that to each pixel its highest respective calculated LAI value is assigned, as expected to be more predominant. On the other hand, an index classification layer has been included, for those pixels with LAI Green, LAI Brown or both LAI Green and LAI Brown estimations within a relative uncertainty threshold of 40%, set by default. The following legend is applied: 0 = out of uncertainty threshold; 1 = LAI *green*, 2 = LAI *green* & *brown*, 3 = LAI *brown*. Finally, a LAI Green/Brown RGB composite map within the applied uncertainty threshold is provided in jpg format.

The robustness and portability of the retrieval models have been positively evaluated for LAI Green and LAI Brown mapping over the four European SENSAGRI test sites: Spain, Italy, France and Poland. LAI products were generated from 2017 to 2018 S2 time series collection. Time series analysis suggests a realistic seasonal LAI evolution over multiple crop types. Finally, the accuracy of the LAI product has been estimated through direct comparison against in-situ data, suggesting a good overall performance for both models (LAI Green RMSE= 0.67 R^2= 0.70; LAI Brown RMSE= 0.43 R^2= 0.62).

As an example, Figure 1 shows a collection of LAI Green/Brown composite maps illustrating the evolution of the total LAI covering a cropland over Valladolid (Spain). First, crops gradually develop until reaching a maximum cover during spring, from when green vegetation decreases as crops start to senescence. Only pixels estimated within a relative uncertainty of 40% are represented. Surfaces as bare soil, clouds and build-up areas are masked out.

Figure 2 presents the LAI Green and LAI Brown temporal profiles of multiple crop types across the different test sites. For crops such as wheat and barley, the vegetation temporal evolution reaches a maximum LAI Green during spring. Next, as LAI Green decreases, LAI Brown emerges and later is extinguished by end of the summer. Overall, the LAI Green and LAI Brown crop evolution describes a seasonal behaviour typical of winter annual crops, which are usually harvested in late spring or summer.

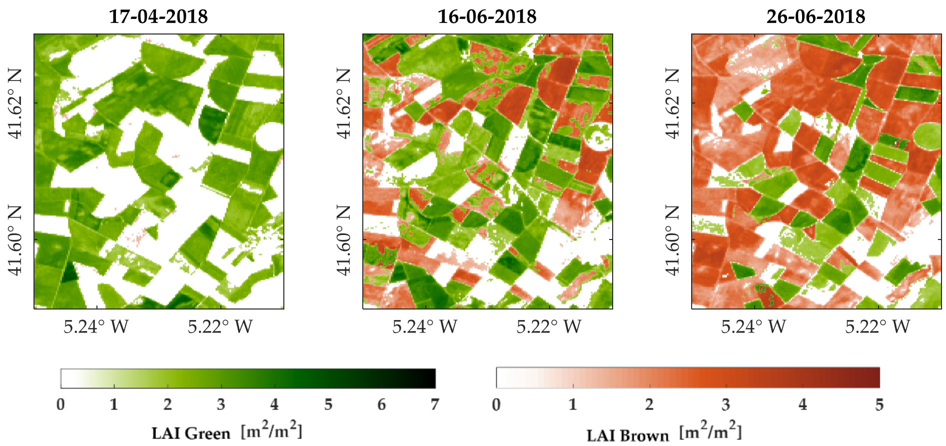

Figure 1. Seasonal evolution of LAI total (LAI Green + LAI Brown) over an agricultural region in Valladolid (Spain).

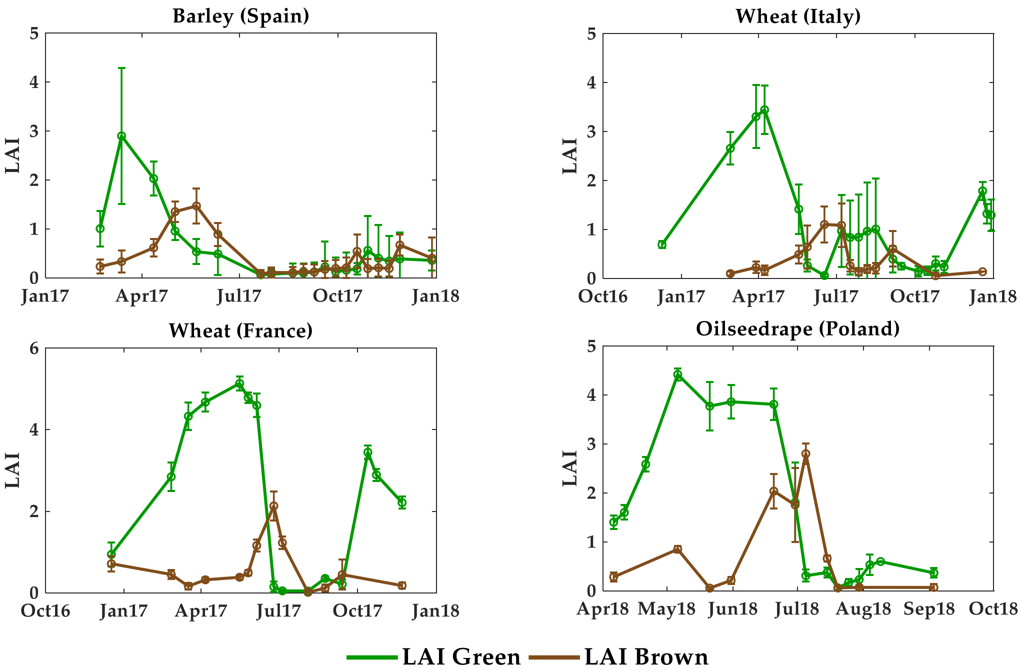

Figure 2. LAI Green and LAI Brown crop temporal profiles.

SENSAGRI Deliverables

D4.06. Final operational LAI prototype exploiting S1 & S2
D4.07. Software of the final operational LAI prototype.
D4.08. Final version of LAI products over test sites in Europe
D4.09. Final LAI Algorithm Theoretical Basis Document.
D7.12. Second Validation of Leaf Area Index Maps

References

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