Vegetation plays an essential role in the study of global climate change influencing terrestrial CO\textsubscript{2} flux exchange and variability through plant respiration and photosynthesis. Therefore, the assessment of current vegetation status is critical in order to foster Earth vegetation protection and restoration initiatives at both local and global scales (García-Haro et al., 2014).

Classical vegetation monitoring methods are not effective to acquire vegetation dynamics because they are time consuming, outdated and often too expensive. During the last years, different remote sensing methods are being employed for biophysical parameters retrieval in order to assess the vegetation status and its dynamics at scales ranging from kilometers to decametric spatial resolutions.

One can find in the literature that biophysical parameters estimation has been conducted using many different approaches (Verrelst et al., 2015): through the empirical relationships between the biophysical parameter of interest and vegetation indices (VIs); using pure statistical regression methods from existing remote sensing observations, products and \textit{in situ} measurements; and inverting physically based radiative transfer models (RTMs) using either look-up tables (LUTs) or machine learning techniques.

In this Thesis, we propose and describe the development of a generic processing chain able to retrieve key biophysical parameters such as Leaf Area Index (LAI), Fraction of Absorbed Photosynthetically Active Radiation (FAPAR) and Fractional Vegetation Cover (FVC). The biophysical parameters are derived from satellite data with different spatial and spectral characteristics useful for appraising Earth vegetation status at both local and global scales within a common procedure. The proposed processing chain for the estimation of these vegetation essential climate variables (ECV) is developed implementing a hybrid method through the inversion of physically-based radiative transfer models with state-of-the-art machine learning regression algorithms. We first generate a database composed of PROSAIL RTM (Jacquemoud et al., 2009) simulations (e.g. reflectances + biophysical parameters) which is used to train non-linear machine learning regression methods. Once the methods are trained, the best
method in terms of accuracy, bias and goodness-of-fit is selected. Then this method is used for biophysical parameter retrieval. In particular, we focus on Gaussian Processes (GPs) for regression (Williams and Rasmussen, 1996) which offer interesting capabilities: not only state-of-the art approximation results, but also the possibility to obtain confidence intervals for the predictions and automatic input bands ranking from the models.

The proposed retrieval chain was successfully applied to retrieve LAI at local scale, in the framework of ERMES (An Earth observeRvation Model based RicE information Service) project (Busetto et al., 2017), using time series of Landsat-7 ETM+ (Enhanced Thematic Mapper), Landsat-8 OLI (Operational Land Imager) remote sensing data at 30 m spatial resolution. Similarly, the retrieval chain was applied using time series of SPOT-5 (Take-5) Sentinel-2A data at 10 m spatial resolution (Campos-Taberner et al., 2016a; 2017). Multitemporal LAI estimates were obtained during the 2015 and 2016 European rice seasons over local rice areas in Spain (Albufera), Italy (Lomellina) and Greece (Thessaloniki), which are responsible of 85% of total European rice production. On the other hand, the proposed chain was also successfully applied to jointly estimate LAI, FAPAR and FVC at 1 km spatial resolution in the framework the Land Surface Analysis Satellite Applications Facility (LSA SAF) project, for an optimal exploitation of the AVHRR/MetOP data at global scale.

In the context of exploiting the technology implemented in smartphones for studies dealing with natural sciences, in this Thesis we propose the use of smartphones for non-destructive LAI measurements through the use of an application called PocketLAI. PocketLAI was successfully tested over rice fields in the 2014 rice season in Spain and was used for acquiring in situ LAI measurements for the validation of the processing chain at local scale during 2015 and 2016 over the three local study areas (Campos-Taberner et al., 2015; 2016b).

In general, LAI estimates derived from the developed processing chain at local scale agree with regard to the 2015 and 2016 seasonal rice phenological cycle and followed the temporal dynamics of the ground measurements. At global scale, the estimates were validated over selected sites located around the planet covering different biomes by intercomparison with reference biophysical products such as MOD15A2, GEOV1 and MSG/SEVIRI. The intercomparison showed high consistency between them which highlighted the chain robustness. Figure 1 shows a LAI map derived from the application of the processing chain at local scale over the Spanish study area using a Sentinel-2A image acquired on August 9, 2016. It can be seen the high spatial detail of estimates which allows to identify different values within the same rice field mainly due to the heterogeneity of the rice field caused by non-homogenous seeding and agro-practices. For its part, Figure 2 shows an example of FAPAR map corresponding to 25 July in 2015 in which global realistic spatial patterns are derived, exhibiting the higher values over Earth dense vegetated surfaces whereas lowest values (virtually zero) over sparse and bare areas.

Figure 1. High-resolution (10 m) LAI map obtained with Sentinel-2A data acquired in the Spanish study area on August 9, 2016.
Both results at local and global scales revealed the operational nature of the developed processing chain and proved the accuracy of the estimates retrieved by the chain. The modularity of the chain opens future research and applications. Future work could consider the application of the chain to ongoing remote sensing missions to cope with new satellite and sensors features at all scales.

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