GAUSSIAN PROCESSES REGRESSION FOR BIOPHYSICAL PARAMETER RETRIEVAL FROM IMAGING SPECTROSCOPY DATA: OPPORTUNITIES FOR SENTINEL-2 AND -3

J. Verrelst, J. Muñoz, L. Alonso, J. Delegido, J.P. Rivera, and J. Moreno

Image Processing Laboratory (IPL), University of Valencia, Spain
jochem.verrelst@uv.es

KEYWORDS: Sentinel-2, Sentinel-3, machine learning algorithms, Gaussian Processes regression (GPR), biophysical parameter retrieval.

ABSTRACT:

ESA’s upcoming satellites Sentinel-2 (S2) and Sentinel-3 (S3) aim to ensure continuity for Landsat, Spot and MERIS observations by providing multispectral and hyperspectral images of high temporal resolution. S2 and S3 will deliver near real-time operational products with a high accuracy for land monitoring, but therefore robust and accurate retrieval methods are needed. Machine learning algorithms may be powerful candidates for the estimation of biophysical parameters because of their ability to adaptive, nonlinear regression. We have compared the efficacy of four state-of-the-art machine learning algorithms given various S2 and S3 band settings and 3 important biophysical parameters: leaf chlorophyll content (Chl), green leaf area index (LAI) and fractional vegetation cover (FVC). Tested Sentinel configurations were: S2-10m (4 bands), S2-20m (8 bands), S2-60m (10 bands) and S3-300m (19 bands), and tested methods were: support vector regression (SVR), kernel ridge regression (KRR), neural networks (NN) and the novel Gaussian processes regression (GPR). GPR was the only method that reached the by GMES defined precision of 10% in the estimation of Chl. Also, although validated with RMSE accuracy around 20%, GPR yielded optimal LAI estimates at highest S2 spatial resolution of 10 m with only 4 bands. GPR did not only outperform the other retrieval methods for the majority of tested configurations, but also provided additional confidences of the estimates, which gives it a key advantage over the other methods.

1. INTRODUCTION

The lifetime of current Earth Observation (EO) sensors such as Landsat, SPOT and MERIS and MODIS are coming to an end. Any gap in data availability would affect on-going monitoring programs. To guarantee the availability of data to service providers and users, Global Monitoring for Environment and Security (GMES) took the initiative to a new generation of environmental Earth Observation missions, the so-called Sentinel missions. Five different Sentinel concepts have been planned. Specifically, Sentinel-2 (S2) and Sentinel-3 (S3) are designed to provide continuity to monitoring services over global terrestrial surfaces by relying on multispectral high resolution (S2) and multispectral medium resolution (S3) observations. At the same time, along with these new missions, there is a demand of enhanced operational retrieval strategies of relevant biophysical parameters (Martimort et al., 2007). Leaf chlorophyll content (Chl), green leaf area index (LAI) and fractional vegetation cover (FVC) are among the most important biophysical parameters retrievable from EO data (Whittaker and Marks; Lichtenthaler, 1987).

When it comes to the implementation of candidate retrieval methods into operational Sentinel data processing chains, crucial is to invest in models that are both predictive and robust. The GMES objective for near real-time delivery requires that the dependency on ancillary data should be kept to the minimum. Empirical methods such as vegetation indices are not generally applicable while inversion of radiative transfer (RT) models requires site-specific information for proper model parameterization, which is not always directly available. Alternatively, machine learning algorithms have the potential to generate adaptive, robust relationships and, once trained, do not need additional information. Typically, machine learning methods are well able to cope with the strong nonlinearity of the functional dependence between the biophysical parameter and reflected radiance.

In this paper, we have tested four state-of-the-art machine learning algorithms given S2 and S3 band settings, which were i) support vector regression (SVR), ii) kernel ridge regression (KRR), iii) Gaussian Processes regression (GPR), and iv) neural networks (NN). Used data came from the ESA-led field campaign SPARC, which took place on the agricultural test site Barrax, Spain. This brings us to the following objective: evaluation of four machine learning algorithms given S2 and S3 simulated data of Agricultural sites. The potential use of the best evaluated algorithm in view of operational processing chains for monitoring services will be further discussed.
2. SENTINEL

2.1. Sentinel-2
Sentinel-2 (S2) capitalizes on the technology and the vast experience acquired with SPOT and Landsat over the past decades (Martimort et al., 2007). S2 is a polar-orbiting, superspectral high resolution imaging mission. The mission is envisaged to fly a pair of satellites with the first planned to launch in 2013. Each S2 satellite carries a Multi-Spectral Imager with a swath of 290 km. It provides a versatile set of 13 spectral bands spanning from the visible and near infrared to the shortwave infrared, featuring 4 bands at 10 m, 6 bands at 20 m and 3 bands at 60 m spatial resolution. Furthermore, S2 incorporates three new bands in the red-edge region, which are centered at 705, 740 and 783 nm. An overview of the band settings is given in Table 1. In full operational phase, the pair of S2 satellites will deliver data taken over all land surfaces and coastal zones every 5 days under cloud-free conditions, and typically every 15-30 days considering the presence of clouds. To serve the objectives of GMES, S2 satellites will provide imagery for the generation of high-level operational products (level 2b/3) such as biophysical variables, e.g. Chl, LAI and leaf water content. To ensure that the final product can meet the user requirements, the GMES user committee defined an accuracy goal of 10% (ESA, 2010).

<table>
<thead>
<tr>
<th>Spectral band</th>
<th>B1</th>
<th>B2</th>
<th>B3</th>
<th>B4</th>
<th>B5</th>
<th>B6</th>
<th>B7</th>
<th>B8</th>
<th>B8a</th>
<th>B9</th>
<th>B10</th>
<th>B11</th>
<th>B12</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band center (nm)</td>
<td>443</td>
<td>490</td>
<td>560</td>
<td>665</td>
<td>705</td>
<td>740</td>
<td>783</td>
<td>842</td>
<td>865</td>
<td>945</td>
<td>1375</td>
<td>1610</td>
<td>21900</td>
</tr>
<tr>
<td>Band width (nm)</td>
<td>20</td>
<td>65</td>
<td>35</td>
<td>30</td>
<td>12</td>
<td>15</td>
<td>20</td>
<td>115</td>
<td>20</td>
<td>20</td>
<td>30</td>
<td>90</td>
<td>180</td>
</tr>
<tr>
<td>Spatial resolution (m)</td>
<td>60</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>20</td>
<td>20</td>
<td>20</td>
<td>60</td>
<td>60</td>
<td>60</td>
<td>20</td>
<td>20</td>
<td>20</td>
</tr>
</tbody>
</table>

Table 1. Sentinel-2 MSI band settings.

2.2. Sentinel-3
The pair of Sentinel-3 (S3) satellites will provide global, frequent and near real-time Ocean, ice and land monitoring. It continues Envisat’s altimetry, the multispectral, medium-resolution visible and infrared ocean and land-surface observations of ERS, Envisat and Spot, and includes enhancements to meet the operational revisit requirements and to facilitate new products and evolution of services. For continuity in land applications, S3 will be equipped with the Ocean and Land Colour Instrument (OLCI), which will provide continuity of the existing MERIS mission plus the inclusion of six new bands (Ferréck et al., 2009). OLCI’s spectral bands are in the visible to near-infrared wavelength range (from 403 to 1040 nm) and with spectral bandwidths ranging from 3.75 to 40 nm. Band settings are provided in table 2. The OLCI ground resolution requirement depends whether the data are acquired above Open Ocean, or coastal zones and land. OLCI products require a spatial resolution at sub-satellite point of 1200 m over Open Ocean, and sea ice and 300 m over coastal zones, while land products require a resolution of 300 m globally.

<table>
<thead>
<tr>
<th>Spectral band</th>
<th>O1</th>
<th>O2</th>
<th>O3</th>
<th>O4</th>
<th>O5</th>
<th>O6</th>
<th>O7</th>
<th>O8</th>
<th>O10</th>
<th>O11</th>
<th>O12</th>
<th>O13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band center (nm)</td>
<td>400</td>
<td>412.5</td>
<td>442.5</td>
<td>450</td>
<td>510</td>
<td>560</td>
<td>620</td>
<td>665</td>
<td>813.75</td>
<td>831.25</td>
<td>708.75</td>
<td>753.75</td>
</tr>
<tr>
<td>Band width (nm)</td>
<td>15</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>10</td>
<td>7.5</td>
<td>7.5</td>
<td>10</td>
<td>7.5</td>
<td>2.5</td>
</tr>
</tbody>
</table>

Table 2. Sentinel-3 OLCI band settings.

3. MACHINE LEARNING ALGORITHMS

Machine learning approaches learn the relationship between the input (e.g. reflectances) and output (e.g. biophysical parameters) by fitting a flexible model directly from the data. The hyperparameters (or weights) of the model are typically adjusted to minimize the error in an independent validation dataset. This way, one looks for the best generalization capabilities, not only a good performance in the training set since this would give rise to an overfitted solution. We considered four state-of-the-art machine learning algorithms for the purpose of comparison, which were i) support vector regression, ii) kernel ridge regression, iii) Gaussian processes regression, and iv) neural networks. All these regression methods are popular in various applicative domains thanks to its relatively fast training, good performance, and robustness to the overfitting problem, though they also have their specific shortcomings. A brief description is given below:

i. The Support Vector Regression (SVR) is the SVM implementation for regression and function approximation (Schölkopf and Smola, 2002; Smola and Schölkopf, 2004).

ii. The Kernel Ridge Regression (KRR), or Least Squares SVM (LS-SVM), is the kernel version of the regularized linear regression (Schölkopf and Smola, 2002; Shawe-Taylor and Cristianini, 2004).

iii. A neural network is a (potentially fully) connected structure of neurons organized in layers, and a neuron is a linear regression followed by a nonlinear function (Haykin, 1999).

iv. Recently, a new machine learning approach that is based on the Gaussian Processes (GP) theory has been introduced in the literature (Rasmussen and Williams, 2006). GP regression (GPR) provides a probabilistic approach for learning generic regression problems with kernels. GPR alleviates some shortcomings of the previous methods, while maintaining very good numerical performance and stability: i) GPR is far more simple than NN, and needs less sample points, ii) Not only a mean prediction for each sample (pixel), but also a full distribution over the output values including an uncertainty of the prediction (confidence interval) and, iii) GPR provide a ranking of features
(bands) and samples (spectra), thus overcoming the blackbox problem. A Matlab implementation of GPs is freely available at http://www.gaussianprocess.org/gpml/.

4. DATA AND EXPERIMENTAL SETUP

4.1. Training and validation database

Ideally, the training and validation database should be representative of actual crops and conditions as observed by the Sentinel sensors. A diverse field dataset, covering various crop types, growing phases, canopy geometries and soil conditions was collected during SPARC (Spectra bARrax Campaign). The SPARC-2003 and SPARC-2004 campaigns took place in Barrax, La Mancha, Spain (coordinates 30°3′N, 28°6′W, 700 m altitude). In the 2003 campaign, carried out on 12-14 July, biophysical parameters were measured within a total of 113 Elementary Sampling Units (ESU) among different crops. ESU refers to a plot size compatible with a pixel size of about 202 m. In the 2004 campaign, carried out on 15-16 July, the same field data were collected within a total of 18 ESUs among different crops. Leaf Chl was derived by measuring within each ESU about 50 samples with a calibrated CCM-200 Chlorophyll Content Meter. Chl values obtained in the SPARC 2003 campaign show good agreement with those obtained in the SPARC 2004 campaign (Gandía et al., 2004). Green LAI was derived from canopy measurements made with a LiCor LAI-2000 digital analyser. Each ESU was assigned to a LAI value, which was obtained as a statistical mean of 24 samples among 9 crops (garlic, alfalfa, onion, sunflower, corn, potato, sugar beet, vineyard and wheat), with field-measured values of LAI that vary between 0.4 and 6.3, Chl between 2 and 55 µg/cm² and FVC between 0 and 1. Further details on the measurements can be found in (Delegido et al., 2008). Additionally, 30 random bare soil spectra with a biophysical (Chl, LAI, FVC) value of zero were added to broaden the dataset to non-vegetated samples.

4.2. Sentinel configurations

Sentinel band settings were simulated on the basis of Compact High Resolution Imaging Spectrometry (CHRIS) data. CHRIS provides high spatial resolution hyperspectral data over the visible/ near-infrared (VNIR) spectra from 400 to 1050 nm. We made use of nominal nadir CHRIS observations in Mode 1 (62 bands, maximal spectral information) for the four SPARC campaign days, where field measurements of surface properties were measured in conjunction with satellite overpasses. CHRIS Mode 1 has a spatial resolution of 34 m at nadir. The images were geometrically corrected (Alonso and Moreno, 2004), followed by atmospheric correction according to the method proposed in (Guanter et al., 2005). The nadir image from 12 July 2003 was used for spectral and spatial resampling to the settings of S2 and S3. The radiometric resolution of CHRIS is 12 bits, which is the same as S2. Because of S2 having bands with varying pixel sizes, and CHRIS having a spectral range only until 1050 nm, simulated Sentinel data according to the following configurations were generated:

<table>
<thead>
<tr>
<th>Sentinel:</th>
<th>S2-10m</th>
<th>S2-20m</th>
<th>S2-60m</th>
<th>S3-300m</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spatial resolution:</td>
<td>10 m</td>
<td>20 m</td>
<td>60 m</td>
<td>300 m</td>
</tr>
<tr>
<td># Bands:</td>
<td>4</td>
<td>8 (4 + 4 at &lt;20 m)</td>
<td>10 (2 + 8 at &lt;60 m)</td>
<td>19</td>
</tr>
<tr>
<td>Band position:</td>
<td>B2, B3, B4 and B8</td>
<td>B2 to B8a</td>
<td>B1 to B9</td>
<td>O1 to O20</td>
</tr>
<tr>
<td>Wvl:</td>
<td>490-665 and 842 nm</td>
<td>490-865 nm</td>
<td>443-945 nm</td>
<td>413-940 nm</td>
</tr>
</tbody>
</table>

Table 3. Sentinel configurations used in this study.

Finally, the ESU data set along with the ensemble of canopy reflectance spectra according to the four Sentinel configurations were divided into a training and validation datasets for parameterization and evaluation of the algorithms. In order to avoid skewed results, each method was 50 times run with different random realizations of training and testing samples according to an 80/20% partition. The machine learning methods were compared against the ordinary linear regression (LR) as a reference. Model’s performance was evaluated with the absolute root-mean-squared error (RMSE) and the relative RMSE (%) to assess accuracy, and the coefficient of determination (r²) to account for the goodness-of-fit. The relative RMSE was used to compare the performances across the different methods and parameters. Additionally the time needed to render the models was recorded.
5. RESULTS

5.1. Method evaluation

Results of the four retrieval methods for Chl, LAI and FVC are presented in figure 2 given the S2 10m (4 bands), S2-20m (8 bands), S2-60m (10 bands) and S3-300m (19 OLCI bands) configurations. It is important to note that the performance of the machine learning algorithms depends on the quality of the training data and can thus vary depending on the fed training data. The error bars provide an idea of the robustness of applied model with respect to the input data. It can be observed that pooling the samples 50 times hardly impacted the model training, but nevertheless had consequences on the performance of the model when applied to validation data. Particularly NN appeared to perform unstable once applied to validation data (e.g. see S2-20m and S2-60m). Hence, of importance is how accurate a trained model performs when validated against ground reference measurements. Given the validation results, for the majority of Sentinel configurations GPR provided best retrieval accuracies. The method outperformed the other retrieval methods with S2-20m and S2-60m configurations in estimating Chl, with all Sentinel configurations in estimating LAI, and with S2-10m configuration in estimating FVC.

Furthermore, note that GPR, SVRR and KRR rendered robust results when having relatively few bands available. In case of LAI and FVC the performance of these methods hardly changed across the different S2 configurations (4, 8 and 10 bands). The relative RMSE stabilized around 20%. This is encouraging as it suggests that the structural variables can be optimally mapped at highest spatial resolution of 10 m with only 4 bands. Effectively, these 4 S2 bands, inherited from Landsat, SPOT and MERIS, are well known for their sensitivity to vegetation properties (ESA, 2010).

Although Chl reached a similar accuracy level of about 20% with S2-10m data, optimal retrievals were not achieved. GPR yielded more accurate Chl estimations with the S2-40m and S2-60m configurations, which include bands in the red edge (B5: 705, nm B6: 740 nm). Hence, this underlines the importance of red edge band with respect to Chl retrieval, but apparently these bands are not that important with respect to structural variables LAI and FVC. From all tested cases, best results were obtained by GPR for the estimation of Chl with the S2-60m configuration. It led to a mean relative RMSE of 10.5% with a standard deviation (SD) of 3.2%, and is on the order of the GMES goal accuracy of 10%. The overall good performance of GPR throughout all Sentinel configurations proved that this method acts as a powerful regressor, not only for hyperspectral data, but also for multispectral data.

In fact, despite having most spectral bands available, S3 did not lead to superior results. Why accuracies were not optimized is probably due to the coarse spatial resolution. The field sampling of SPARC was not designed for this spatial scale.

![Figure 2](image_url)

Figure 2. RMSE [%] results (mean and _1 SD) Chl (left), LAI (middle) and FVC (right) retrievals using LR, KRR, GP and NN for the configurations of S2-10m (top), S2-20m (second), S2-60m (third) and S3-300m (bottom).
5.2. Processing time

Apart from the delivered accuracy, another criterion for being a successful candidate into an operational processing chain is the processing speed. To evaluate this, for each configuration the time to compute model training and validation was recorded. All calculations were done in a Matlab environment on a Windows XP Intel(R) Core(TM)2 Quad CPU, 2.4 GHz, 3.00 GB RAM processor. Ordinary linear regression hardly took computational time. Also KRR proved to be a fast regressor (0.6 sec.) whereas SVR needed considerably more time, particularly when having only 4 bands available (11 sec.). Though, these models run still fast compared to NN. The complex optimization during the learning process of the network occurred at the expense of a long computational time. While the computation of S2-10m took about 6.4 sec., its computational load started to become increasingly costly when more bands were included. The computation time of S3-300m took on average 55 sec. The long processing time of training a model is a major disadvantage of NN, although once the NN is calibrated its application on actual data is almost instantaneous. In comparison, GPR computed up to 27 times faster than NN. S3-300m was computed in about 2 seconds. S2-10m was even computed in less than one second. This fast running time suggests that GPR is computationally efficient. Summarizing, from the four tested regression methods provided GPR the most accurate estimations and with a relatively fast running time. Therefore, the parameter retrieval performances of GPR across the different Sentinel configurations will be further analyzed in the next section.

5.3. Pixel-wise retrievals of biophysical parameters using GPR

GPR was used to pixel-wise estimate the three parameters Chl, LAI and FVC given the Sentinel configurations. For each biophysical parameter and Sentinel configuration a single GPR model was trained and validated and then run over the simulated Sentinel image. Parameter retrieval was completely automated and image-based. Excellent validation accuracies were obtained with the estimation of Chl. RMSE stayed well below the by GMES defined threshold of 10% for the configurations of S2-20m, S2-60m and S3-300m (7.1, 8.3 and 6.6%). Validation accuracies of structural parameters stayed stable around 23% (LAI) and 17% (FVC) throughout the different Sentinel configurations.

Figure 3 provides maps of the retrieved parameters for the different Sentinel cases. To start with the most detailed maps of the S2-10m configuration, within-field variations in biophysical canopy properties throughout the landscape are clearly perceivable by the three parameters. Particularly in Chl the pronounced spatial variation clearly marks the irrigated circular fields with green biomass. These irrigated fields are characterized by a Chl above 40, a LAI above 3 and a FVC above 60%. Areas with low Chl, LAI and FVC (the blueish parts) are mainly bare soils, fallow lands or rainfed senescing or harvested cereal fields (wheat, barley).

The coarser S2-60m maps show essentially the same spatial patterns with about the same magnitudes of estimates. For instance, the circular fields and within-field variability are still clearly observable. These examples demonstrated that the unique band setting of S2 proved its use for crop monitoring applications. More spectral bands can be added at the expense of only a small pixel coarsening with the benefit of improved retrievals.

Considerably coarser maps were obtained with the S3-300m configuration. For instance, only a few pixels spanned the circular fields. Although within-field spatial information has been mostly lost, spatial patterns of the irrigated fields were still observable. Nevertheless, small differences in retrievals as a consequence of the coarsening were notable. Chl retrievals no longer exceeded 60 µg/cm², most likely due to the merging of green irrigated areas with dry non-irrigated areas, leading to composite pixels. Such composite pixels are expected to occur frequently at the medium spatial resolution of S3, thereby smoothing out field-level variations.
5.4. Corresponding pixel-wise confidence values using GPR

A unique feature of GPR is that it provides along with the estimates associated confidence values. These confidence values provide pixel-wise an indication of the familiarity with what has been presented during the training process. Here, a confidence value expresses the standard deviation (SD) that accompanies the mean estimation of a parameter and provides an idea of the (dis)similarity as compared to the spectra that was used for the model training. Figure 4 shows the confidence maps corresponding to the estimation maps of figure 3. To facilitate visual comparison, the maps were color scaled to an SD that is half of their corresponding estimates. In these maps areas with reliable retrievals are clearly distinguishable from areas with uncertain retrievals. Most reliable retrievals were found on irrigated areas and harvested fields. Retrievals with poor reliability were found on areas with remarkably different spectra that were not included during the training process, such as bright, whitish calcareous soils (center, right), or harvested rainfed barley fields with remaining bright straws covering the surface (center). Hence, in practice, the associated confidence maps detect areas that may benefit from a denser sampling regime.

Because of the same data used, the confidence maps enabled to compare the performance across the different Sentinel configurations. Overall, LAI and FVC retrievals provided the same degree of confidences across the different Sentinel configurations. The Sentinel band settings seems thus not to affect the retrieval reliability of these parameters. Conversely, the estimation of Chl led to poorer confidences using S2-10m data compared to Sentinel configurations with more bands (note the brighter blue color tones across the whole map). This is probably due to the aforementioned suboptimal band setting of S2-10m for this parameter compared to the other Sentinel configurations (no bands in red edge; see also figure 2 and table 4). Note that LAI, much more than the other parameters, suffered from poor confidences over the whitish calcareous soils in the right part of the image. FVC only had little problem with these soils when having only 4 bands available at S2-10m, afterwards the confidences over these areas considerably improved.
The upcoming S2 and S3 missions open opportunities to implement improved retrieval algorithms in operational processing chains. Of interest are retrieval algorithms that are transparent, accurate, fast, robust, and are sufficiently flexible to make fully use of the new S2 and S3 bands. Machine learning algorithms are able to cope with most of these specifications. Four state-of-the-art machine learning algorithms (SVR, KRR, GPR, NN) were compared given various Sentinel configurations. GPR was evaluated as best performing method for the biophysical parameters Chl and LAI. Only slightly better accuracies were achieved with SVR in estimating FVC.

Despite the promising performances of GPR for Sentinel band settings, it should nevertheless be emphasized that the employed simulated Sentinel data was only based on a spectral and spatial resampling of CHRIS data. This implies that the Sentinel-2 bands B10, B11 and B12 and Sentinel-3 bands O1 and O21 were not included in the analysis. Although these bands aim to function for atmospheric correction purposes and are of less importance for biophysical parameter retrievals, GPR may also be able to capture spectral variation in these bands that could be useful for biophysical parameter retrieval. Especially bands in the NIR and SWIR (B10, B11, B12 and O21) are known to be sensitive to soil and vegetation structure (Bannari et al., 2006), and can thus contribute to the retrieval of LAI or FVC.

Apart from band position, Sentinel bands are also configured with different radiometric accuracies (e.g. signal-to-noise) than the CHRIS sensor. This is particularly the case for the S2 calibration bands at 60m configurations (B1 (443 nm), B9 (945 nm), B10 (1375 nm) that are configured for atmospheric applications, such as aerosols correction (B1), water vapour correction and cirrus detection correction (B9 and B10) (ESA, 2010). These atmospheric bands are typically discarded in physically-based biophysical retrieval approaches because being more sensitive to aerosols than vegetation properties (e.g. see Richter et al., 2009). Machine learning approaches such as GPR make full use of the available variation embedded in each single band, meaning that even those atmospheric bands can be exploited for retrieval of biophysical parameters.

To end with, although GPR was evaluated as best performing algorithm, more powerful retrieval methods may exist that deserve to be tested. Regardless of the outcome, however, until now none of the comparable methods possesses the interesting feature to deliver additional confidence maps. This gives GPR a key advantage over other retrieval methods. Moreover, these confidence maps easily allow evaluating the robustness of the generated models by applying the same trained model over images acquired in other conditions. Resulting confidence maps provide then an indication on how well retrievals are realized in other conditions.

7. CONCLUSION

ESA’s upcoming satellites Sentinel-2 (S2) and Sentinel-3 (S3) aim to replace and improve the old generation of satellite sensors by providing superspectral and hyperspectral imagery of high temporal resolution. S2 will be configured with band settings according to Landsat, Spot and MERIS, while S3 will include a sensor similar to MERIS. Moreover, both Sentinels will be equipped with additional new bands for improved retrieval capacities. Along with these enhanced sensor configurations, there is also a need for improved parameter retrieval methods implementable into operational processing chains. We have compared four state-of-the-art machine learning regression algorithms (SVR, KRR, GPR, NN) for the estimation of key biophysical parameters Chl, LAI and FVC. Hyperspectral CHRIS data was simulated according to the following S2 and S3 configurations: S2-10m (4 bands), S2-20m (8 bands), S2-60m (10 bands), and S3-300m (19 bands). GPR not only yielded best accuracies for the majority of cases but also proved to be a fast regressor. It was found that LAI
and FVC can be mapped at highest spatial resolution of 10 m with four bands. Chl benefited from extra bands in the red edge for reaching best estimates. Specifically, Chl reached RMSE accuracies on the order of the by GMES requested precision threshold of 10%. Beyond high accuracies, GPR possesses the unique feature to provide along with a mean estimation a confidence value, which makes it a very promising candidate for implementation into operational Sentinel processing chains.

8. ACKNOWLEDGMENTS

J. Verrelst is supported by the FP7-PEOPLE-IEF-2009 grant (Grant Agreement 252237).

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