REACHING STAGE 4 OF VEGETATION PRODUCT VALIDATION BY EXPLOITING THE SYNERGY BETWEEN UAV, HR SATELLITES AND IOT MEASUREMENTS

Marie Weiss1, Wenjuan Li2, Sylvain Jay1, Fernando Camacho3, Hongliang Fang4, Frédéric Baret1

1 UMT CAPTE, UMR 1114 EMMAH, INRAE, Avignon, France
2 HIPHEN, Avignon, France
3 EOLAB, Valencia, Spain
4 LREIS, Institute of Geographic Sciences and Natural Resources Research, CAS, Beijing, China

ABSTRACT

We present and discuss some recent developments to reach the ultimate validation stage as defined by the Land Product Validation group of the Committee on Earth Observation Systems (CEOS LPV) for vegetation products. We specifically focus on the complementarity between the exhaustive spatial sampling provided by Unmanned Aerial Vehicles (UAVs) or high-resolution satellite data and the exhaustive temporal sampling available with IoTs.

Index Terms—validation, LAI, chlorophyll, fIPAR fractional green vegetation cover, IOT, UAV

1. INTRODUCTION

Following the recommendations of the CEOS-LPV, vegetation biophysical variable products such as Leaf Area Index (LAI) and fAPAR (fraction of Absorbed Photosynthetically Active Radiation) reached validation stage 3 for medium resolution sensors. This indicates that product inter-comparisons are performed globally, validation against ground measurements is performed over a significant number of sites (more than 30), allowing the characterization of product uncertainties, and common validation practices are well established [1]. Up to now, these practices rely on:

(i) Selecting a set of around 50 local ground measurements distributed over a given validation site, each of them having a footprint of around 10 x 10 m². Then, the ground measurements are scaled up with at least decametric resolution satellite data over a 3 x 3 km² area, using empirical relationships established between ground measurements and multispectral reflectances and/or vegetation indices.

(ii) inter-comparing the several products existing at similar spatial resolution over a selection of sites representative of the Earth surface for different years [2].

Regarding the ground validation, the main limitations rely on the manpower and associated costs that induce a low spatial and temporal representativeness of the different biomes and environmental conditions (soil, climate, human practices). Moreover, as the scaling up of the local ground measurements is performed with ancillary decametric resolution data, the independency between the ground truth and the product is not ensured. Finally, the performances of these empirical relationships are limited by the spatial sampling strategy over the full validation area. Although the product inter-comparison at the global scale is an added value, it is also limited by the fact that these products are derived from similar data (e.g. reflectance in a selection of wavelengths) and share some similar hypothesis. In other words, the products may agree between themselves but may not represent the actual value of the biophysical variables. This has also been studied from a theoretical point of view, based on the use of 3D RTM models by Widlowski et al [3].

Recently, the validation work was completed by several initiatives to better understand the uncertainties related to ground measurements. In particular, the CEOS-LPV has defined the concept of “super sites” that gathers several international initiatives such as NEON, TERN, or GBOV [4, 5], together with the concept of Fiducial Reference Measurements (FRM) [6]. Thanks to a huge effort on measurement strategies including the multiplicity of devices and spatial sampling, FRMs are intended to provide very accurate measurements over the same super sites throughout the seasons and years. However, regarding the considerable efforts required for FRMs,
complementary validation measurements, well disseminated over the globe, seasons and years are still needed.

We present recent developments that could contribute to perform these complementary ground measurements, by using cost-effective means to ensure better temporal and spatial samplings, and providing more independent ways to scale up ground local measurements.

2. EXHAUSTIVE SPATIAL SAMPLING WITH UAV AND VHR SENSORS

The recent availability of very high-resolution (VHR) data at a reasonable cost opens new facilities to support medium-resolution data validation. This includes data of different natures (RGB, multi or hyperspectral, LiDAR) acquired by sensors on board Unmanned Aerial Vehicles (UAVs) or very high-resolution satellites such as PLANETSCOPE and SKYSAT.

This kind of data can be used in a similar way as previously, e.g., by establishing empirical relationships between local ground measurements and VHR data to scale-up the biophysical variable values over the validation area. They present the advantages of a very good temporal resolution (few days) as well as an improved spatial resolution (few cm to 3 m). This helps solving issues related to the sensor characteristics such as the temporal sampling to allow a good consistency between the time of ground and VHR acquisitions, as well as a good matching between the footprints of the ground measurements and the sensor characteristics (e.g., spatial resolution, point spread function).

Additionally to the classical empirical transfer functions, UAV can be exploited to provide more independent means of measurements. For example, structure from motion algorithms applied to RGB cameras allow deriving 3D point clouds with a sufficient accuracy to derive the fraction of intercepted PAR (fIPAR) and thus, LAI [7]. RGB images can also be exploited by applying segmentation techniques to estimate the green vegetation fraction in different directions and then derive LAI or fAPAR. Moreover, the very high resolution of RGB images can be combined with the spectral information of multispectral images characterized by a lower spatial resolution to better assess the canopy vegetation variables, including LAI, fAPAR, and canopy chlorophyll content [8]. As UAVs allow covering the whole validation area, it represents an exhaustive and independent mean of validation. Less independent but still very interesting for the spatial coverage and the resolution, the multispectral information acquired on board an UAV can also be used to estimate vegetation variables from model inversion techniques as demonstrated in [9-11].

In order to optimize UAV data performances, protocols for image acquisition and processing must be followed, especially regarding the flight configuration, the camera settings such as integration time as well as the sensor calibration and by ensuring stable illumination conditions during the flight [12]. Although very effective, UAVs have some drawbacks related to manpower, weather conditions (wind, rain) and legislation (some sites cannot be flown). This may still constitute a limitation to provide a sufficient temporal monitoring of the ground measurement sites to assess the CEOS validation stage 4.

3. EXHAUSTIVE TEMPORAL SAMPLING WITH IOTS

Recent developments in IoTs (Internet of Things) made new autonomous devices available to measure continuously ground vegetation variables. For instance, the PASTIS-57 (PAI Autonomous System from Transmittance Instantaneous Sensed from 57°, [13-15]), the LAINet [16], or DCPs [17] sensors have shown good capabilities for continuous monitoring of LAI and fAPAR. They are based on transmittance measurements in a single wavelength and processed based on the gap fraction theory to derive LAI and fAPAR. More recently, [18] used continuous microspectrometer measurements to invert a radiative transfer model by exploiting the multispectral and directional information obtained with the variation of the illumination conditions throughout the day.

Such devices provide the same kind of measurements as the devices used in classical validation protocols (e.g., DHPs, AccuPAR, LAI2000…) and similar accuracies are thus expected. However, processing algorithms must take into account the inevitable varying illumination conditions that may impact the estimation of the transmittance or reflectance. Furthermore, as IoTs allow estimating LAI and fAPAR every day, compositing algorithms may be required since these variables are expected to show slow and continuous variation over time if no anthropic event occurs [16, 18].
Like for manual devices, the main limitation relies on the spatial sampling strategy that depends on the number of available devices. Therefore, similarly to manual ground measurements, auxiliary information is required for the scaling up of the data over the entire validation area. [16] fitted an empirical transfer function between LANDSAT NDVI and several automatic ground measurements over an entire season, assuming that the temporal sampling will compensate for the spatial sampling as only 12 instruments were available. In the same way, [17] fitted a linear relationship between the average value of automatic ground measurements made at three locations with manual measurements over 33 locations supposed to represent the whole area made at seven dates throughout the season. However, to achieve their goal, these two studies make strong assumptions about the spatial and temporal behavior of LAI over the studied sites.

The use of IoTs therefore requires the setting up of a spatial sampling strategy regarding the different sources of heterogeneities of the vegetation variables. This heterogeneity can be characterized by acquiring images at the very beginning of the season and for previous seasons. Using either satellites such as SENTINEL-2 or PLANETSCOPE or much higher resolution of UAV, these data should help making the distinction between permanent heterogeneities (e.g., soil type) and non-permanent (land cover or management practices if they exist) to optimize the IoTs spatial sampling.

4. CONCLUSIONS

As briefly described in this paper, recent technological developments show high potential to reach CEOS validation stage 4 by (i) increasing the temporal and spatial representativeness of the validation site networks, (ii) and providing more independency between ground and satellite measurements. It is however required to assess their accuracy using the fiducial reference measurements of the CEOS super sites. Protocols and guidelines for these novel approaches should be elaborated by the community and contribute to the CEOS LAI validation protocol document.

Although both UAVs and IoTs reduce the manpower issue, they still represent a significant cost effort to deploy a network of medium-resolution sensor product validation sites with sufficient temporal and spatial representativeness at the global scale. Indeed, IoTs still require the use of auxiliary high-resolution data to compensate for the low spatial sampling. More developments are thus needed to better exploit the synergy between those data. Spatio-temporal fusion methods should be developed similarly to what has been done for decametric and kilometric sensors [19-21]. Finally, these tools are much better suited for the validation of decametric resolution sensors. There is indeed a high potential in gathering a large amount of data, at least for agricultural sites where more and more farmers are equipped with IoTs or UAV for precision farming purposes. Once validated with uncertainties characterized, the decametric products could then be used as reference to infer medium sensor product accuracy.

5. ACKNOWLEDGEMENTS

We acknowledge the Centre National d’Etudes Spatiales (CNES) for the financial support of this research through a research grant under the program TOSCA (Terre solide, Océan, Surfaces Continentales, Atmosphère).

6. REFERENCES

[1] R. Fernandes, S. Plummer, J. Nightingale, F. Baret, F. Camacho, H. Fang, S. Garrigues, N. Gobron, M. Lang, R. Lacaze, S. LeBlanc, M. Meroni, B. Martinez, T. Nilson, B. Pinty, J. Pisek, O. Sonnentag, A. Verger, J. Welles, M. Weiss, J.-L. Widlowski, G. Schaepman-Strub, M. Roman, and J. Nickeson eds., “Global Leaf Area Index Product Validation Good Practices - Version 2.0,” Committee on Earth Observation Satellites. Working Group on Calibration and Validation. Land Product Validation Sub-Group, 2014, p. 75.

[2] M. Weiss, F. Baret, and A. Verger, “BELMANIP2: Enhancement of the CEOS-BELMANIP ensemble of sites used for the validation of land products from medium resolution sensors.”

[3] J.-L. Widlowski, “On the bias of instantaneous FAPAR estimates in open-canopy forests,” Agricultural and Forest Meteorology, vol. 150, no. 12, pp. 1501-1522, 2010/12/15/, 2010.

[4] B. Bayat, F. Camacho, J. Nickeson, M. Cosh, J. Bolten, H. Vereecken, and C. Montzka, “Toward operational validation systems for global satellite-based terrestrial essential climate variables,” International Journal of Applied Earth Observation and Geoinformation, vol. 95, pp. 102240, 2021/03/01/, 2021.

[5] L. A. Brown, C. Meier, H. Morris, J. Pastor-Guzman, G. Bai, C. Lerebourg, N. Gobron, C. Lanconelli, M. Clerici,
and J. Dash, “Evaluation of global leaf area index and fraction of absorbed photosynthetically active radiation products over North America using Copernicus Ground Based Observations for Validation data,” Remote Sensing of Environment, vol. 247, pp. 111935, 2020/09/15/, 2020.

[6] P. W. Thorne, H. J. Diamond, B. Goodison, S. Harrigan, Z. Hausfather, N. B. Ingleby, P. D. Jones, J. H. Lawrimore, D. H. Lister, A. Merlone, T. Oakley, M. Palecki, T. C. Peterson, M. de Podesta, C. Tassone, V. Venema, and K. M. Willett, “Towards a global land surface climate fiducial reference measurements network,” International Journal of Climatology, vol. 38, no. 6, pp. 2760-2774, 2018/05/01, 2018.

[7] Y. Che, Q. Wang, Z. Xie, L. Zhou, S. Li, F. Hui, X. Wang, B. Li, and Y. Ma, “Estimation of maize plant height and leaf area index dynamics using an unmanned aerial vehicle with oblique and nadir photography,” Annals of Botany, vol. 126, no. 4, pp. 765-773, 2020.

[8] S. Jay, F. Baret, D. Dutartre, G. Malatasta, S. Hénó, A. Comar, M. Weiss, and F. Maupas, “Exploiting the centimeter resolution of UAV multispectral imagery to improve remote-sensing estimates of canopy structure and biochemistry in sugar beet crops,” Remote Sensing of Environment, vol. 231, pp. 110898, 2019/09/15/, 2019.

[9] C. Lelong, P. Burger, G. Jubelin, B. Roux, S. Labbé, and F. Baret, “Assessment of Unmanned Aerial Vehicles Imagery for Quantitative Monitoring of Wheat Crop in Small Plots,” Sensors, vol. 8, no. 5, pp. 3557-3585, 2008.

[10] A. Verger, N. Vigneau, C. Chéron, J.-M. GilliloT, A. Comar, and F. Baret, “Green area index from an unmanned aerial system over wheat and rapeseed crops,” Remote Sensing of Environment, vol. 152, pp. 654-664, 2014/09/01, 2014.

[11] B. Xu, J. Li, T. Park, Q. Liu, Y. Zeng, G. Yin, J. Zhao, W. Fan, L. Yang, Y. Knyazikhin, and R. B. Myneni, “An integrated method for validating long-term leaf area index products using global networks of site-based measurements,” Remote Sensing of Environment, vol. 209, pp. 134-151, 2018/05/01, 2018.

[12] M. Weiss, F. Baret, S. Madec, and W. Li, “The problem of radiometric calibration for UAV observations acquired under changing illumination conditions,” in 5th international Remote Sensing (RAQRSV), Torrent, Spain, 2017.

[13] A. Simic, F. Baret, M. Weiss, R. Lecerf, A. Alessandrini, J. F. Hancoq, and O. Marloie, "Production of the high resolution maps of biophysical variables based on SPOT imagery and in-situ measurements generated by PASTIS 57 for Hyttyila, Finland,” pp. 7655-7658.

[14] B. Brede, J.-P. Gastellu-Etchegorry, N. Lauret, F. Baret, J. G. P. W. Clevers, J. Verbesselt, and M. Herold, “Monitoring Forest Phenology and Leaf Area Index with the Autonomous, Low-Cost Transmittance Sensor PASTiS-57,” Remote Sensing, vol. 10, no. 7, 2018.

[15] H. Fang, W. Liu, W. Li, and S. Wei, “Estimation of the directional and whole apparent clumping index (ACI) from indirect optical measurements,” ISPRS Journal of Photogrammetry and Remote Sensing, vol. 144, pp. 1-13, 2018/10/01, 2018.

[16] G. Yin, A. Li, H. Jin, W. Zhao, J. Bian, Y. Qu, Y. Zeng, and B. Xu, “Derivation of temporally continuous LAI reference maps through combining the LAINet observation system with CACAO,” Agricultural and Forest Meteorology, vol. 233, pp. 209-221, 2017/02/15, 2017.

[17] Y. Ryu, J. Verfaillie, C. Macfarlane, H. Kobayashi, O. Sonnentag, R. Vargas, S. Ma, and D. D. Baldocchi, “Continuous observation of tree leaf area index at ecosystem scale using upward-pointing digital cameras,” Remote Sensing of Environment, vol. 126, no. 0, pp. 116-125, 2012.

[18] W. Li, M. Weiss, S. Jay, A. Comar, J. Labrosse, J. Gillet, R. Lopez-Lozano, G. Deshayes, B. De Solan, S. Madec, and F. Baret, “GAI, LCC and CCC monitoring over wheat fields from continuous sub-hourly spectrometers measurements,” Agricultural and forest meteorology, submitted, 2021.

[19] F. Gao, J. Masek, M. Schwaller, and F. Hall, “On the blending of the Landsat and MODIS surface reflectance: predicting daily Landsat surface reflectance,” IEEE transactions on geoscience and remote sensing, vol. 44, no. 8, pp. 2207-2218, 2006.

[20] W. Li, F. Baret, M. Weiss, S. Buis, R. Lucaze, V. Demarez, J.-f. Dejoux, M. Battude, and F. Camacho, “Combining hectometric and decametric satellite observations to provide near real time decametric FAPAR product,” Remote Sensing of Environment, vol. 200, no. Supplement C, pp. 250-262, 2017/10/01, 2017.

[21] Á. Moreno-Martínez, E. Izquierdo-Verdiguier, M. P. Maneta, G. Camps-Valls, N. Robinson, J. Muñoz-Mari, F. Sedano, N. Clinton, and S. W. Running, “Multispectral high resolution sensor fusion for smoothing and gap-filling in the cloud,” Remote Sensing of Environment, vol. 247, pp. 111901, 2020/09/15, 2020.