OPTICAL REMOTE SENSING REQUIREMENTS FOR OPERATIONAL CROP MONITORING AND YIELD FORECASTING IN EUROPE

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ABSTRACT

The European Commission requires in-season crop yield forecasts at a European level as part of the decision making process on market intervention and for policy support. For the past twenty years, the Monitoring Agricultural Resources (MARS) Unit of the European Commission Joint Research Centre (JRC) has operationally produced such forecasts using the MARS Crop Yield Forecasting System (MCYFS), a modelling infrastructure driven by agro-meteorological data and assisted by remotely sensed observations. The potential of quantitative assessments of crop canopy status by remote sensing is currently underexploited in MCYFS because the available data do not satisfy the requirements for crop specific monitoring and yield forecasting. After presenting the current MCYFS, this paper discusses these ideal data requirements with the objective to see how the forthcoming Sentinel3-OLCI data could satisfy them.

1. INTRODUCTION

Agricultural monitoring was probably the first civilian application of satellite remote sensing data. Indeed, the Large Area Crop Inventory Experiment (LACIE) realized by the USA with multispectral imagery obtained from the first Landsat platform demonstrated how it could be used to estimate wheat production [1]. The potential of multitemporal measurements of reflected radiation for estimating primary production in general was quickly recognized, as it well-known that the leaf properties that determine the radiation-interception characteristics of plant canopies are directly linked to photosynthesis, stomatal resistance and evapotranspiration and can be inferred from measurements of reflected solar energy [2]. Harvested crop yield can be estimated from satellite remote sensing information to a certain extent. But such approach can only take into account the yield determining factors that are linked to the crop status, as it is observed by the satellite imaging instrument. A different application is crop monitoring, in which crop status in the current year is compared to that of previous years.

The information that can be gathered in a timely manner using such technology is valuable for decision making purposes. The European Commission requires in-season crop information at a European level as part of the decision making process on market intervention and for policy support. In 1988 the Council of Ministers of the European Union decided to create the MARS project (initially standing for Monitoring Agriculture by Remote Sensing) designed to apply emerging space technologies for providing independent and timely information on crop areas and yields. For the past twenty years, the MARS Unit (now standing for Monitoring Agricultural Resources) of the European Commission Joint Research Centre (JRC) has operationally produced such yield forecasts, thus contributing towards a more effective and efficient management of the Common Agricultural Policy. Since 2000, the expertise in crop yields has been applied outside the EU. Services have been developed to support EU aid and assistance policies and provide building blocks for a European capability for global agricultural monitoring and food security assessment.

The yield forecasting activities over Europe rely on what has become known as the MARS Crop Yield Forecasting System (MCYFS). The details of how this system works will be presented in a section hereafter. Despite the initial focus of the MARS project on remote sensing, it was gradually recognized that various technological limitations were complicating quantitative crop yield predictions and crop specific monitoring based on satellite imagery at the European scale [3], and the development of the system was therefore steered towards an agro-meteorological approach based on crop growth simulations. It can now be resumed to a spatialized crop growth modelling infrastructure driven by agro-meteorological data and assisted by remotely sensed observations.

Nowadays, technological progress is allowing the possibility to send into orbit a vast array of imaging instruments with increasingly diversified characteristics, thereby changing the way in which we can observe and monitor the Earth. In this respect, a great deal is expected from the Sentinel missions planned within the Global Monitoring for Environment and Security (GMES) programme: the most ambitious operational Earth Observation programme to date [4]. These new possibilities, and particularly the Ocean and Land Colour Imager (OLCI) on-board of Sentinel-3 [5], have the potential to change how optical remote sensing is

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used in MCYFS for crop monitoring and forecasting yield. Currently, quantitative optical remote sensing is underexploited because the available data does not satisfy a series of technical requirements for crop monitoring and yield forecasting. The objective of this paper is to present these requirements and to discuss how these could be meet by the upcoming OLCI instrument on-board of Sentinel-3.

2. MARS CROP YIELD FORECASTING SYSTEM

The MCYFS is a decision support system driven by expert knowledge and relying on four main pillars: a meteorological data infrastructure, a remote sensing data infrastructure, a crop simulation infrastructure and a statistical infrastructure. The system uses meteorological data to run crop growth models that provide information on crop status, such as biomass production, soil moisture or biomass of the storage organs. Remote sensing provides an independent assessment of crop status through the use of global and pan-European low-resolution imagery in near real-time (NRT). Finally, the statistical infrastructure includes methods used to analyse, along the season, historical yield records against the information about crop status generated by crop models and, in some cases, remote sensing, to produce a forecast that is presented in a monthly bulletin to decision-makers in Brussels. A schematic representation of this process is presented in Figure 1. The system is articulated by a spatial framework defining the spatial reference upon which all the data is generated (reference grids, administrative units, static spatial layers used by crop models and remote sensing, etc.).

2.1. Meteorological infrastructure

This first infrastructure of the system produces spatial information of key meteorological variables for crop development (temperature, rainfall, wind speed, solar radiation, etc.) with a daily time step. The information is generated either from spatially interpolated weather observations from meteorological stations (*circa* 4000 in Europe with data arriving in NRT) or from numerical meteorological model simulations and forecasts provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). The output of the weather monitoring is used in two ways: (1) as input for crop simulations in order to evaluate the effects of weather on crop yields; and (2) as weather indicators to make a direct evaluation of alarming situations such as drought, extreme rainfall during sowing, flowering or harvest etc. A more detailed description of the meteorological infrastructure is available in [6].

2.2. Crop simulation infrastructure

Several crop growth models are embedded in the crop simulation infrastructure of MCYFS. These complex groups of algorithms simulate crop growth and provide indicators such as the total biomass produced, the

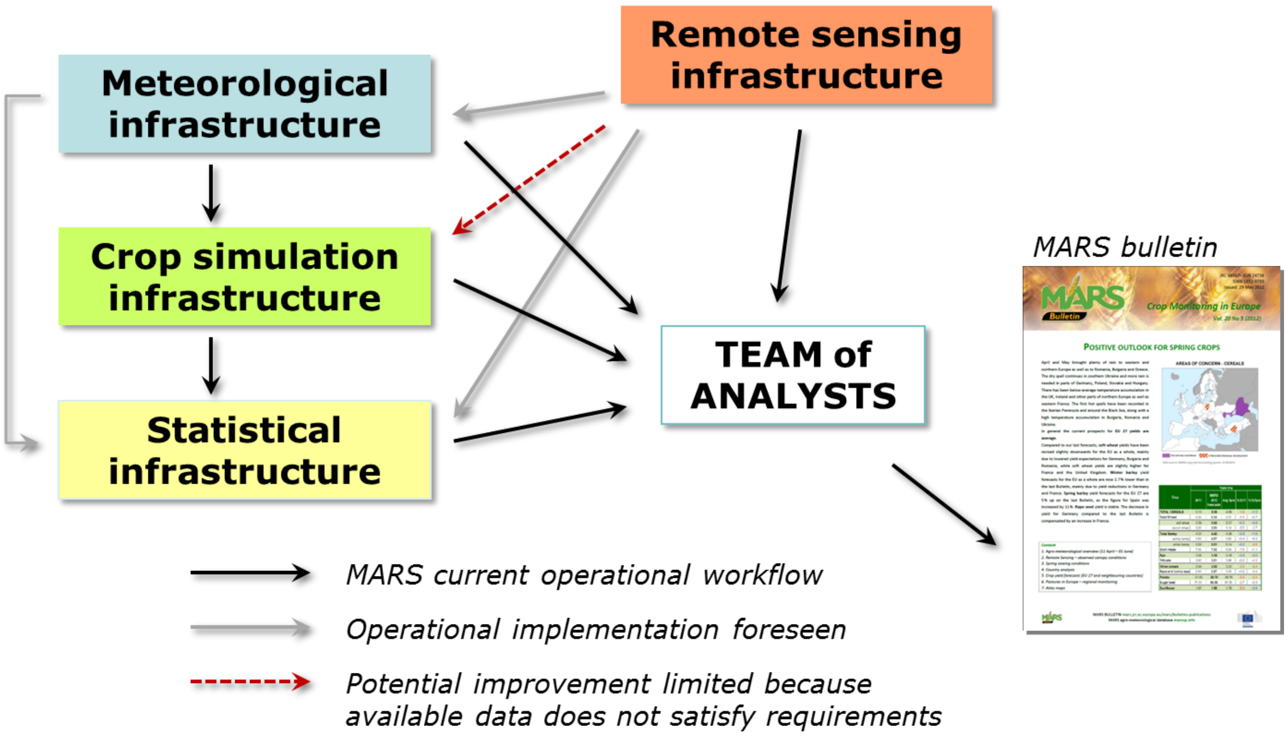

Figure 1 Current and foreseen workflow of the MARS Crop Yield Forecasting System (MCYFS)

biomass of the storage organs, crop development stage, etc., using daily weather data from the meteorological infrastructure as an input. Soil information, crop parameters and crop management data are also necessary to run the models to account for the effects of changes in soil water content and crop management. The models used within the MCYFS are point models but they are connected with spatial databases that make them spatially explicit, thus simulation units are defined based on the intersection of meteorological grid cells and soil units where the crop is present. The results are presented either at the level of the simulation unit or aggregated to various administrative units up to national levels. The main model used in the MCYFS is WOFOST (WOrld FOod Studies) [7]. Within the MCYFS, WOFOST simulates development from emergence until harvest for different annual crops: namely wheat, barley, sunflower, maize, rapeseed, potato, and sugar beet through the calibration of crop-specific parameters such as the effect of thermal time on assimilation coefficients, root depth or partitioning fractions. Rather than producing a specific value describing the actual harvested crop yield, the models calculate a set of indicators describing the inter-annual variability of crop biophysical parameters that can be statistically related to official yield figures to produce forecasts. Further details on the crop simulation infrastructure are summarized in [8].

2.3. Statistical infrastructure

The statistical infrastructure gathers the statistical methods and software that enable to establish a relationship between indicators of current growing conditions with historical time series of official harvested crop yields at national level. These time series are first detrended. This trend represents the influence of long-term economic and technological dynamics (such as increased fertiliser application, improved crop management methods, new high yielding varieties, etc.) on crop yields. The residual inter-annual variation is assumed to be largely explained by the impact of weather on crop growth. This variation is to be explained by indicators from the other MCYFS infrastructures. In practice the indicators used are essentially obtained from the crop growth simulation results (such as potential or water limited dry weight of the simulated biomass or storage organs). Two different statistical approaches are used: (1) a classic regression analysis between yield and one or more indicators; and (2) a scenario analysis in which only the years that were similar to analysed year, with respect to selected agro-climatic events as represented by the indicators, are used to predict the yield. More details on the statistical infrastructure can be found in [9].

2.4. Remote sensing infrastructure

Remote sensing data is currently used mostly in a qualitative way, as an independent source of information. The main role of remote sensing is to monitor vegetation status, to confirm the behaviour of crop growth indicators from the crop simulation infrastructure and to identify regions with anomalies. To do so, a selection of remote sensing indicators is computed from satellite images in near real time (NRT) with dedicated algorithms and methods. The indicators include the Normalized Difference Vegetation Index (NDVI) but also a biophysical variable with a real physiological meaning: the fraction of Absorbed Photosynthetically Active Radiation (fAPAR). These are mostly, but not exclusively, calculated from SPOT-VGT imagery at 1 km of spatial resolution. An historical archive of these products was built and is continuously updated in order to catch the variability in time for the target regions. Valuable information about anomalies is derived from the comparison of the various parameters for the current season with the ones of historical year, the previous year or exceptional years (e.g. absolute and relative differences, frequency analysis). More details on the remote sensing infrastructure are available in [10].

Currently, remote sensing is not directly linked to the other infrastructures in the current operational workflow. The main reason, as it is developed in the next section of this paper, is that the remote sensing data currently available does not satisfy some criteria necessary for crop monitoring and yield forecasting applications. However, some degree of integration is already pursued. In the meteorological infrastructure, snow coverage data derived from MSG-SEVIRI products are already used to complement ground station weather data. Recent work has shown that incoming solar radiation, also derived from MSG, could also improve and replace station data as input for crop growth models [11], [12]. In the crop simulation infrastructure, the convergence of the phenological trends and anomalies calculated by the model with the ones observed from the satellite can either strengthen the confidence in the model outputs validity or indicate where the model performs poorly. An example of the latter is the case of winter kill, which is not simulated in the models but can be seen in drops of fAPAR and NDVI. Regarding interaction with the statistical infrastructure, cumulated fAPAR has recently been used as proxy of biomass production to evaluate the state of pastures with respect to the historical dataset. Under specific conditions, the same data is used in regression with historical crop yields in order to predict final harvest for the given season.

3. IDEAL REQUIREMENTS OF OPTICAL RS

A more quantitative use of satellite remote sensing in MCYFS is currently limited because the available data does not satisfy the 4 requirements exposed hereafter. Overall, these ideal requirements are considered to be common for both foreseen uses of remote sensing in MCYFS, namely for crop monitoring purposes and as a predictor in yield forecasting, even though some differences may exist. These requirements are not to be confused with those of crop area estimation, which are also necessary in operational agriculture monitoring, but are not considered in this paper.

3.1. An adequate crop specific signal over large geographic areas

A major hurdle towards using remote sensing for quantitative crop monitoring and yield forecasting is the high fragmentation of Europe's agricultural landscapes. This complicates the extraction of a crop specific signal from many satellite imaging instruments that can provide timely information over large geographic areas, because such sensors typically have a coarse spatial resolution close to 1 km (*e.g.* NOAA-AVHRR and SPOT-VGT). With such sensors, interpreting the signal can be ambiguous since it is composed of a mixture of several land cover types. While the onset of winter crops in early spring may be detectable in mixed pixels (since their strong increase in near infrared (NIR) reflectance will dominate the signal with respect to the bare soil of adjacent summer crops), the temporal trajectory of summer crop reflectance will be much more complicated to follow since it will be mixed in variable proportions with adjacent summer crops. The mixture not only varies from place to place, but also in time, as the phenological responses of adjacent crops may not be synchronised from one year to another. A further complication comes from the many types of crops potentially side by side, and which change from one year to another according to crop rotations. A timely identification of such changes would require dedicated methodologies leveraging on a combination of high spatial, temporal and spectral resolutions that will become available through the joint use of instruments on-board of Sentinels-2 and 3, and perhaps even Sentinel-1, which will have a synthetic aperture radar (SAR) instrument.

Defining the adequate spatial resolution for any application is not trivial. Some authors, *e.g.* [13], propose to use geostatistics to quantify the spatial heterogeneity of the landscape and thus find the sufficient pixel size to capture the major part of the spatial variability. Another approach, designed more specifically to agricultural monitoring purposes, proposes to focus directly on the target crop fields in agricultural landscapes by seeking simultaneously the coarsest acceptable pixel size and the acceptable level of pixel purity, which is the degree of homogeneity of the signal with respect to the target crop [14]. By focusing on where observation footprints fall adequately with respect to the target fields, this approach leads to larger tolerable ground sampling distances than what traditional Shannon-Nyquist sampling theory would dictate. A full-blown survey based on such approach to define adequate spatial resolution for major agricultural landscapes across the globe (and within Europe) still remains to be done. However, it is generally recognised that "medium" spatial resolution sensors (i.e. ~300m, such as ENVISAT-MERIS, Terra/Aqua-MODIS and the upcoming Sentinel3-OLCI), offer the potential to move significantly closer to monitoring fields in many parts of the world, rather than monitoring the general agricultural landscape as it is done currently with 1 km instruments. By selecting only the pixels that fall adequately in the fields, the possibility of extracting a crop specific signal from MODIS has been demonstrated over a highly fragmented landscape in Europe [15]. An attempt to couple this information with the modelling solutions in MCYFS has resulted in a partial success [16], but needs to be further explored and extended geographically. However, this demonstration exercise relied on a crop mask available only after harvest. Work is therefore still necessary to identify, in a NRT context, where time series with a pure enough crop specific signal can be found.

Beyond the spatial resolution, having an adequate crop specific signal also requires an adequate spectral resolution. While the red and NIR bands necessary for monitoring biomass are generally ubiquitous in optical satellite Earth observation instruments, other bands can be highly desired in order to ensure the quality of the signal, e.g. blue or thermic bands are useful to make proper atmospheric corrections and cloud masking. Some bands can be desired to provide finer information on crop stress, such as the SWIR band which informs on the water content of the vegetation. Finally, as already suggested before, a certain amount of spectral bands can be valuable to properly identify crops in order to provide a valid crop specific signal.

3.2. Frequent observations in near real time

Monitoring crop status requires updated information at a high temporal frequency in near real-time (NRT). This is necessary in order to grasp the quick changes that can occur during the growing season as crops respond to the weather and the management practices that they are subjected to. Within a week, a field can accumulate a substantial amount of biomass if the crop is in a fast growing developmental stage, such as stem elongation for cereals. Similarly, the phenological state of a crop like rapeseed can quickly change from emergence to flowering, when the risk of yield loss due to rain becomes much higher. In order to monitor such events in a timely manner, the information should be available 1-3 days after acquisition by the satellite. This NRT requirement may limit the sophistication of the data processing that can be tolerated. Methods must favour a certain degree of computer efficiency over absolute accuracy for operational purposes. However, a long term data archive is also necessary to compare current conditions with past situations. This archive is not subject to the NRT constraints and can thus be reprocessed *a posteriori* to guarantee higher quality standards.

Having information at a weekly interval seems adequate in agronomic terms. However, unlike SAR imagery, optical satellite remote sensing instruments cannot "see" through clouds, and is therefore limited to cloud-free periods. Further observations have to be discarded because they do not satisfy some viewing geometry constraints. Satellites need to acquire observations practically at a daily time frequency so that, at least over most of Europe, there is some data at a desired time step of approximately 7 days. This imposes a limit to the spatial resolution, as discussed in the previous section, since most sensors providing daily revisit frequency, such as SPOT4/5-VGT, NOAA/Metop-AVHRR and Terra/Aqua-MODIS, have a coarse spatial resolution ranging from 250 m to 1 km. It could be argued that for some cloudy regions in Europe, several observations during a single day would be necessary to ensure cloud-free periods are adequately exploited. Currently, this can be achieved with geostationary meteorological satellites, such as MSG, but at the expense of a spatial resolution of several kilometres.

When observations are available, having access to the individual daily (or near-daily) observations would be preferred over having predefined image composites. A temporal composite is a common way to present remote sensing information over a large area without having the problem of missing data. However, compositing is usually done with a unique and global solution (i.e. a given algorithm and with a fixed time period) delivered by the data provider to ensure temporal and spatial consistency across applications. Having access to the daily data could enable the creation of customized temporal syntheses that are adapted to the specific application of crop monitoring, e.g. by choosing optimal compositing parameters based on cloud coverage and seasonality as proposed by [17]. Yet, traditional compositing by itself could be avoided altogether for monitoring purposes. In a typical compositing approach, a given number of potential observations are resumed to a single value over a fixed compositing period. This has the effect of diluting the temporal precision of the information. In a 10-day composite using the popular maximum value compositing (MVC) technique [18] that is currently used in the MCYFS, a single observation is selected to represent each 10-day period. The result is a time series where observations separated by anything from 1 to 20 days are artificially considered as occurring every 10 days. Furthermore, when more than one valid observation are available, it is a pity to discard them simply to satisfy the compositing criteria. Individual observations could be more adequately exploited by temporally interpolating them using either a smoothing algorithm (an overview of these is available in [19]), fitting simplified models of the canopy dynamics (e.g. [20], [15]) or even assimilating them into deterministic crop growth models (see [21] for a review). The length of the compositing period can also limit data availability in NRT. A method that enables to satisfy such NRT requirements would be a temporal synthesis based on a moving window that gives the highest weight to the most recent observation

3.3. Long term warranty on data continuity

The investment needed to implement an operational system typically requires some warranty on data continuity. Unfortunately, current optical instruments generally do not have such mandates. The MODIS instruments on Terra and Aqua have been flying for longer than their 6-year projected lifetime. In this case, the successor VIIRS has been placed into orbit in time, but not within the projected lifetime of its predecessors. MERIS on-board of ENVISAT ceased to transmit information earlier this year, long after its projected life expectancy, but before its successor, OLCI, could take over to continue providing similar data. OLCI is also expected to provide products that continue the legacy SPOT-VGT products. Yet the VGT instruments have also expired according to their projected lifetime and may cease to function before OLCI is in orbit. To avoid this sort of data gap, the Belgian Science Policy Office and ESA decided to send a small satellite, PROBA-V, equipped with a reduced-mass version of the VGT instrument, to provide a daily overview of global vegetation growth. These issues on data warranty do not occur for the AVHRR instrument for which NOAA has an operational mandate. Meteorological satellites have similarly provided long term warranty that their products would remain available, thus allowing the development of products for operational use. The arrival of the operational mandate of ESA over the Sentinels is therefore most welcome for institutions like the JRC requiring operational services.

3.4. Interoperability of products

Land surface remote sensing applications still have the tendency to rely only on a single imaging instrument. With the increasing quantity and diversity of instruments set in orbit, such approach underexploits the potential synergies of using jointly different sources of remote sensing data in what have become known as 'virtual constellations'. A prerequisite for that is to have interoperable remote sensing products, i.e. products derived from the respective reflectance of different sensors but that ultimately are independent from these. The result is that an algorithm can be transposed (and adapted if necessary) from one instrument to another to provide a same product which is spatio-temporally consistent irrespectively of which instrument was used. Interoperability of products means that particularities of an instrument, such as the fact that OLCI will be constantly tilted at an angle to avoid sun glint when observing the ocean, are taken into account in the algorithms. To adequately implement such algorithms, it is necessary that characteristics of the imaging instruments, such as particularities of the viewing geometry, of the modulation transfer function and the spectral response curves, are easily made available to the wider scientific community.

With respect to the type of products to have, crop monitoring applications would favour biophysical variables, such as fAPAR and Leaf Area Index (LAI). Unlike vegetation indices, these variables have a real physiological meaning: they govern the process of photosynthesis and the exchange of energy, water and carbon between the canopy and the atmosphere. LAI and fAPAR are going to be part of the Operational GMES Land Monitoring Core Service [22], but for monitoring crops in Europe, it is necessary to have these at the adequate spatial and temporal resolutions discussed previously. In the case of OLCI, this would be at its native spatial resolution of 300 m and with either daily (or near-daily) individual observations, or with a compositing method that enables to satisfy NRT requirements.

Ideally, LAI and fAPAR products generated from different remote sensing datasets and based on different algorithms should produce intercomparable products. This means existing products, such as the CYCLOPES [23], MODIS [24] and the fAPAR product currently used operationally in MARS (based on [25]), could be used simultaneously to produce an ensemble of fAPAR estimations, like it is done with global circulation models for climate change predictions. However, recent work evaluating the agreement between fAPAR time series obtained from the same instrument, but with different algorithms based on different biophysical assumptions, has concluded that such time series only have low to moderate spatio-temporal agreement [26]. For crop monitoring purposes, the absolute value of the fAPAR estimation is not as important as its spatio-temporal consistency. This is because fAPAR is generally only used in relative terms, as an indicator of anomalies, by comparing current values with those of a long term average. Therefore, for crop monitoring it is probably preferable to produce a long term archive of the past, by using algorithms based on the same assumption but capable of being adjusted to various sensors (such as AVHRR, VGT, MODIS, VIIRS and OLCI), rather than using an ensemble of fAPAR products with intrinsically different assumptions.

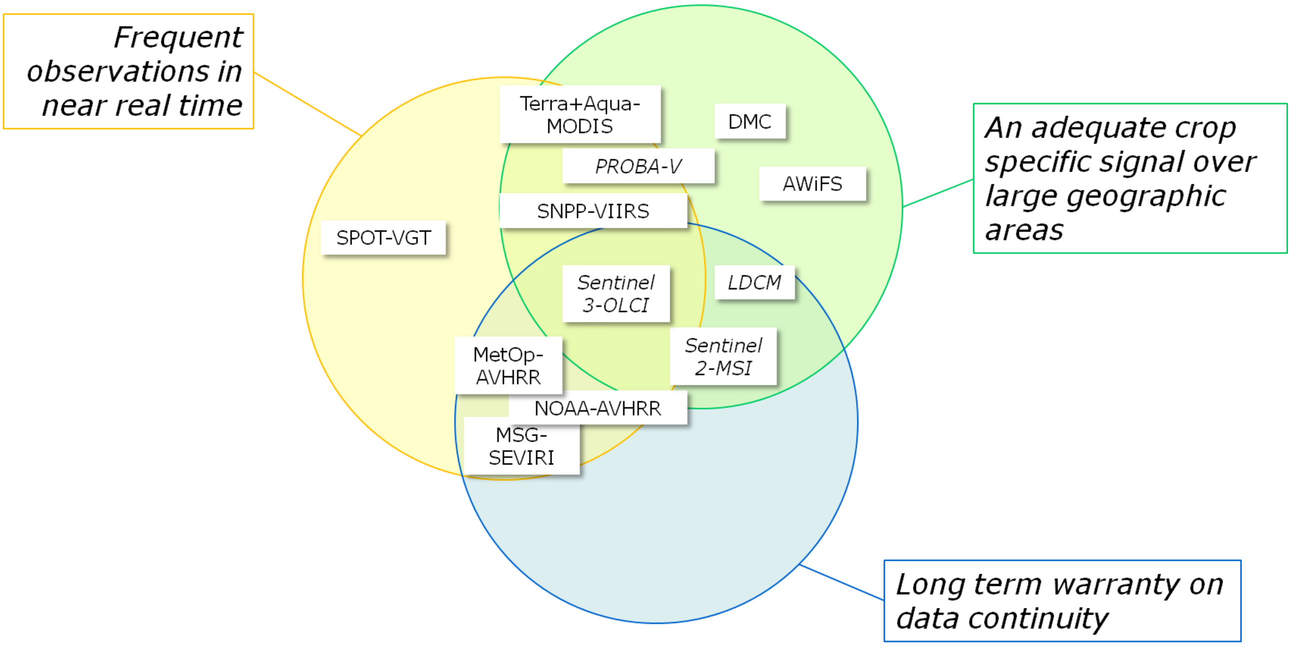

Figure 2 Examples of current and foreseen (in italics) imaging instruments classified with respect to how they satisfy three requirements for operational crop monitoring and yield forecasting. The fourth requirement mentioned in the text, regarding the interoperability of remote sensing products, is omitted for the sake of simplicity and because it is more related to the availability of algorithms and services rather than to the technical specifications of satellite instruments.

4. CONCLUSION

The OLCI instrument has a clear potential to become a very valuable tool for operational yield forecasting and crop monitoring within MCYFS. As shown in Figure 2, Sentinel3-OLCI should, in principle, satisfy the 3 first requirements regarding the technical specifications of the satellite mission. With the GMES core land services providing operationally biophysical variables such as fAPAR and LAI with a global coverage, the fourth requirement could also be covered. However, it is necessary that such variables be provided at the native spatial (300 m) and temporal (near-daily) resolutions that will be possible when two Sentinel3 missions will be simultaneously in orbit. A clear way forward will be to develop algorithms that can exploit synergistically information coming from both Sentinel3 and Sentinel2, and perhaps even Sentinel1, thereby fully justifying the ambitious scope of the GMES programme, at least for agricultural monitoring.

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