



WG2: Protocols for handling biased observations and gap filling in long-term satellite time-series

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1. Introduction

The general aim of working group 2 (WG2) of the Senseco initiative is to improve the time-series processing of satellite sensor data for modelling vegetation processes related to seasonal productivity. This includes phenology (timing of vegetation growth stages) as well as the production of green foliage biomass and relationships with the carbon cycle. This aim will be achieved by using a combination of satellite data from old and new sensors (e.g. Sentinel-2, Sentinel-3), with temporal spectral observations from ground-based towers and instruments on low-flying aerial platforms (UAVs). By closing the temporal gap between day and season, a better understanding of the spatiotemporal changes of plant photosynthetic rate will be achieved linking the objectives of WG2 to those of WG1.

To achieve an optimal and efficient use of satellite time-series, the generation of continuous fields in time and space starting from irregularly distributed data is of critical importance (Figure 1). In reality, several factors influence the acquisition process, resulting in incomplete datasets due to: (1) inadequate climatic conditions (clouds, snow, dust and aerosols), (2) instrumentation errors, (3) losses of image data during data transmission, or (4) low temporal resolution (i.e. long interval needed to revisit and acquire data for the exact same location), among others.

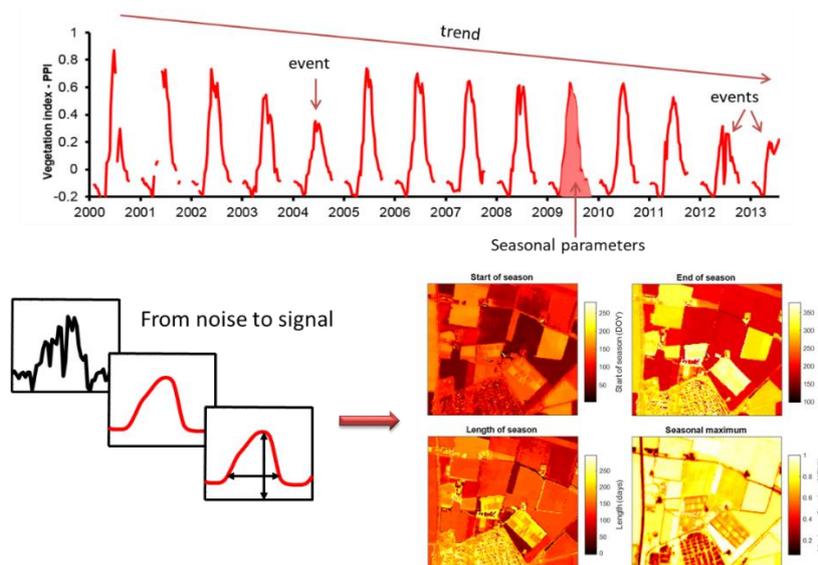


Figure 1: Concept of spatiotemporal information from satellite time-series. The top figure illustrates different interesting components in a time-series of satellite data – trend, sudden events, and seasonal shape. The data are from a birch forest in N. Scandinavia, under attack by defoliating insects. The bottom figures illustrate how we go from a noisy time-series to seasonal parameters describing phenology and productivity of an area for Sentinel-2 data (source: Jönsson et al, 2018).

Over the past years several research teams have developed methods and procedures often implemented in toolboxes to reconstruct or improve incomplete satellite time-series datasets. During the first activities of WG2, an effort has been made to improve the understanding of biases in satellite data time-series caused by cloud and atmospheric influences, and decide how to address them in the subsequent processing. As a follow-up, robust methods/tools for gap-filling and modelling satellite observations in time, and methods for the quantification of temporal representation uncertainty have been identified, taking into consideration the biases observed in the data.

During the first WG2 workshop in Wageningen in February 2019, the participants exchanged experiences with satellite time-series processing from different EO data sources and presented a broad range of applications for satellite time-series. The DATimes toolbox was presented by the University of Valencia as an example how different processing methods could be adopted to handle biased observations, apply gap filling and derive phenological parameters from the time-series data. In the second WG2 workshop in Toulouse in February 2020, the group of participants identified relevant biases and often found biases, relevant methods how to address these and finally different already available toolboxes for time-series analysis were presented and hands-on exercises with general available datasets or own datasets were executed. Based on this workshop, a selection of relevant robust methods/tools for gap-filling and modelling satellite observations in time, was identified. Also an overview of relevant time-series toolboxes was prepared as a starting point for further elaboration of a review paper describing the trends in remote sensing time-series analysis.

This document summarizes the WG2 results related to the deliverable D2.1 which is aiming to deliver protocols for handling biased observations and gap filling in long-term satellite time-series.

As part of the Senseco WG2 activities several papers have been prepared which cover this topic. This document is meant as overview and summary for these papers. The following papers have been prepared:

- ✚ Belda, S., Pipia, L., Morcillo-Pallares, P., Pablo Rivera-Caicedo, J., Amin, E., De Grave, C., and Verrelst, J., 2020. DATimeS: A machine learning time series GUI toolbox for gap-filling and vegetation phenology trends detection. *Environmental Modelling and Software* 127 (2020) 104666 (<https://doi.org/10.1016/j.envsoft.2020.104666>).
- ✚ León-Tavares, J., Roujean, J.L., Smets, B., Wolters, E., Toté, C., and Swinnen., E., 2020. *Remote Sensing* (submitted)
- ✚ Pipia, L., Belda, S., Franch, B., and Verrelst, J., 2021. Trends in satellite sensors and image time series processing methods for crop phenology monitoring. In: *Information and Communication Technologies for Agriculture—Theme I: Sensors*, Springer.

2. Overview of protocols for long-term satellite time-series

2.1 Time series software packages

In general, modelling the phenological evolution from long-term satellite time-series represents a challenging task mainly because of time series gaps and noisy data (Belda et al., 2020), coming from different viewing and illumination geometries, cloud cover, seasonal snow and low temporal resolution (León-Tavares et al., 2020).

Several time series software packages have been developed over the last two decades, with capabilities of identifying phenology trends or disturbances, e.g. TIMESAT (Jönsson and Eklundh, 2004), BFAST (Verbesselt et al., 2010), TIMESTATS (Udelhoven, 2011), SPIRITS (Eerens et al., 2014), BeeBox (Arundel et al., 2016), phenor (Hufkens et al., 2018), pyPhenology (Taylor, 2018), CroPhenology (Araya et al., 2018), FORCE (Frantz, 2019), Earth Engine App (Li et al., 2019), EO Time Series Viewer (Jakimow et al., 2020) (Table 1).

In most cases, these packages are freely available to process time series but they also face some limitation such as the need to use regular time series with more than one phenological cycle, the absence of graphical user interface (GUI) or being merely addressed to advanced users. Also, these packages provide limited tools for gap-filling and smoothing purpose (Belda et al., 2020).

Table 1: Overview of time series processing toolboxes as identified during the Senseco WG2 workshop in Toulouse, February 2020.

Toolbox	Functionality	Implementation	Reference
Timesat	Gapfilling/indicators	Stand alone (open source)	Jönsson and Eklundh, 2004
TimeStats	Indicators/analysis	IDL toolbox (IDL virtual machine) (open source)	Udelhoven, 2011
BFAST	Indicators/analysis	R library (open source)	Verbesselt et al., 2010
DATimes	Gapfilling/indicators/analysis/visualization	Stand alone (open source)	Belda et al., 2020
EOTSA	Indicators/analysis/visualization	WPS + QGIS (open source) / + R library (dev)	Leopold et al., 2020

2.2 Decomposition and Analysis of Time Series Software

Recently and also as part of the Senseco initiative, the DATimes toolbox has been published and made available (Belda et al., 2020). The so-called Decomposition and Analysis of Time Series Software (DATimeS) is a stand-alone image processing GUI toolbox written in MATLAB. This toolbox can model and analyze regular and irregular time series data from complete images, specific region of interest or single pixels in multiple formats (e.g., geotiff, ENVI). It encompasses a suite of powerful mathematical fitting algorithms such as machine learning regression algorithms (MLRAs; e.g., decision trees, kernel-based methods, neural networks) as well conventional fitting methods such as harmonic analyses (HA) (i.e. Fourier Transform (Roerink et al., 2000; Zhou et al., 2012, 2015)) and non-linear least squares regression, i.e. double logistic function (Richardson et al., 2009). With these smoothing and fitting algorithms, spatiotemporal gap-filling can be achieved. DATimeS enables to perform advanced time series tasks for: (1) the generation of spatially continuous maps from discontinuous data, i.e. gap-filling, and (2) detection of heterogeneous spatial patterns of phenological indicators (i.e., crop key growth stages) throughout multiple seasons (Figure 2).

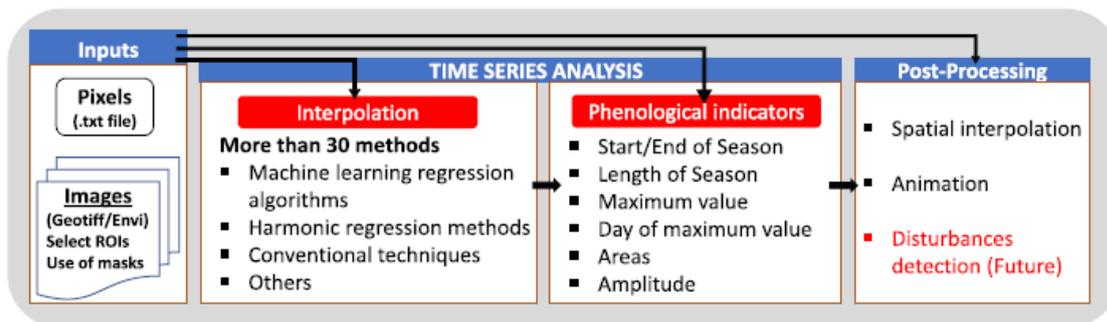


Figure 2: Available time-series analysis functionality within DATimes (source: Belda et al., 2020).

The main functions for preparation of the time-series as described in DATimes are:

1. Filtering options based on cloud thresholding and masking: the time series data can be inspected on missing values, typically due to cloud cover. The first step is to identify the cloudy pixels and to remove by setting their weight to zero.
2. Interpolation is the main processing step of DATimeS: it allows to perform the time series gap-filling (Figure 3). About 30 interpolation algorithms have been brought together and categorized according to the following methods: (1) machine learning regression algorithms (MLRAs), (2) harmonic regression

methods, (3) conventional interpolation methods, and (4) others. Their complete list is reported in Belda et al. (2020).

3. Finally, in the post-processing module, options are provided for spatial interpolation, and time series animation.

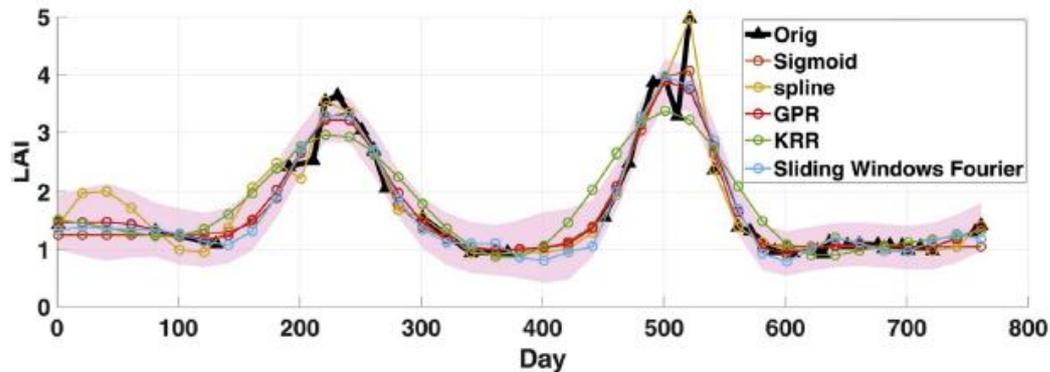


Figure 3: Original and reconstructed time series of LAI using several gap-filling techniques. The example applies different time settings. Interpolated values of time series at a higher sampling frequency (every 20 days). The GPR uncertainties are shown in red shade areas (source: Belda et al. 2020).

2.3 Correction of directional effects in satellite time series datasets

Because of their very large imaging swath, the time series of spaceborne sensors like VEGETATION are not likely to observe the same target with an unique Sun-target-sensor geometry configuration over time. The acquisition geometry for natural targets with such a wide swath can be significantly different even between satellite overpasses. This can seriously hamper the interpretation of observed temporal changes in surface reflectance and derived NDVI time series. The paper by León-Tavares et al. (2020) describes a methodology to perform a BRDF correction (removal of directional effects inferred by land surface anisotropy) to the NDVI time series derived from the three VEGETATION sensors. Applying the BRDF correction leads to reduce the noise observed in the NDVI time-series for the regions under study. The proposed methodology is computationally efficient to operate at global scale a BRDF-corrected NDVI product from VEGETATION sensor long-term series with a follow-on in the frame of the Copernicus Sentinel-3 satellite constellation.

3. Alternative remote sensing time-series datasets

During the WG2 workshops in Wageningen and Toulouse, several participants also provided examples of alternative remote sensing time-series datasets not obtained through a satellite platform. The alternatives ranged from in-situ camera's (e.g., phenocam; Figure 4) and sensors (e.g., The fluorescence box (FloX)) on the ground to the increased use of Unmanned Aerial Vehicle (UAV) platforms for monitoring of crop fields (Figure 5) and natural ecosystems with a range of camera types. These data sources are critical for cal/val studies in relation to satellite time-series or to validate the results of remote sensing based ecosystem and agronomical models. Also for these alternative time-series datasets, acquisition problems arise related to missing or disturbed data points. The question is to which extent the same approaches, procedures and toolboxes can be adopted as for satellite time-series data, or that alternative approaches and functions need to be prepared. This point will be further explored during the WG2 time-series data comparison exercise which is planned for the period January-May 2021.

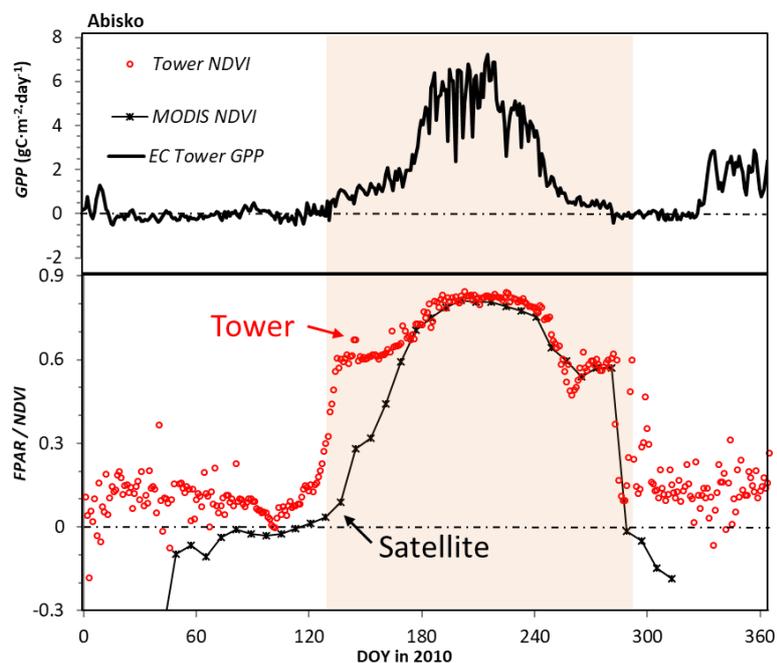
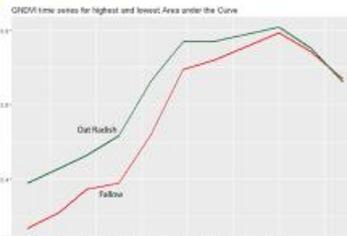
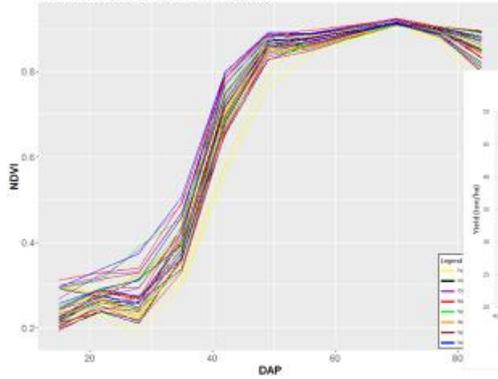


Figure 4: Comparison of ground NDVI from a 15-m mast, MODIS NDVI, and GPP estimated from flux tower measurements. Note discrepancy between satellite and tower measurements in spring (source: Eklundh et al., 2011)



HIGH RESOLUTION UAV TIME SERIES FOR CROP MONITORING TO EVALUATE PLANT-SOIL FEEDBACK IN A POTATO EXPERIMENT

NDVI time series for individual plots



Yield compared to area under the curve for GNDVI with threshold on pixels >0.3

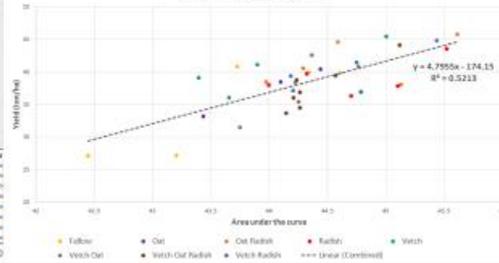


Figure 5: Case study on the application of multi-spectral UAV time-series data to quantify end-of-season potato yield at the experimental plot level.

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