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A Time Composite Algorithm for FAPAR products

Theoretical Basis Document

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1 Introduction

1.1 Purpose

This Algorithm Theoretical Basis Document (ATBD) describes an algorithm used to retrieve information on the nature and properties of vegetated terrestrial surfaces from an analysis of time series of surface product values.

Time series of surface products derived from the interpretation of satellite data operating in the solar domain suffer sporadically from a lack of information due to, for instance, the presence of clouds. A time composite procedure is therefore needed in order to enhance the geographical coverage by simply accumulating for any desired location on the Earth, the informatoion which is available during the compositing period.

Monitoring the state and evolution of the vegetation cover is traditionally done with the Normalized Difference Vegetation Index (NDVI). Many applications have relied on this index for numerous purposes over the last 20 years or so. It has long been known, however, that this index is quite sensitive to perturbing factors such as changes in soil colour, atmospheric effects, or to the particular geometry of illumination and observation at the time of data acquisition (*e.g.*, Huete 1988; Kaufman and Tanré 1992; Pinty et al. 1993; Goel and Qin 1994; Leprieur et al. 1994). The usual technique adopted to derive time composite values of NDVI are based on the so-called maximum NDVI (Holben 1986) procedure. It aims at limiting the effects of some, but not all, of these undesired perturbations and it generally introduces strong biases in the retrieval of the composited surface value (*e.g.*, Meyer et al. 1995).

The time composite algorithm which is proposed here follows a simple strategy that can be used for various surface products such as the daily surface albedo (*e.g.*, Pinty et al. 2000) and, more specifically, the instantaneous FAPAR and "rectified" products extracted from data taken by the SeaWiFS (Gobron et al. 2002a), MERIS (Gobron et al. 2002a), VEGETATION (Gobron et al. 2002b), and GLI (Gobron et al. 2002c) sensors.

This document identifies the sources of input data, outlines the physical principles and mathematical background justifying this approach, describes the proposed algorithm, lists the assumptions and limitations of this technique.

1.2 Algorithm identification

The algorithm described below is called the Time Composite FAPAR algorithm. It is suitable for any surface applications requiring the monitoring of the state of the land surfaces with a revisit time of a few days or more.

1.3 Scope

This document outlines the algorithm recommended to generate a time composite FAPAR product associated to the rectified red and near-infrared reflectances.

1.4 Revision history

The current version, version 1.0, is the first release of this algorithm.

1.5 Other relevant documents

The proposed algorithm has been developed and tested by Pinty et al. (2000) and Gobron et al. (2001). A specific application against daily SeaWiFS retrievals can be found in Gobron et al. (2002b).

2 Algorithm overview

2.1 Objectives of a time compositing technique

For a number of surface applications, it is desirable to ensure a good geographical coverage, which implies the temporal compositing of product time series to fill out gaps in the daily products created by clouds or any other undesirable conditions identified by the proposed flagging strategy. Such a procedure is justified to the extent that studied surface change can occur on a time scale much longer than the one adopted for the compositing. A wisely designed procedure may also allow the retrieval of surface quantities less corrupted by short-term variations, *e.g.*, those due to limitations in correction for atmospheric and angular perurbations.

Various strategies can be proposed to provide an estimate of the most representative state of the medium over the compositing period, *e.g.*, computing the temporal average value or reporting any alternate quantity derived from simple statistical analysis of the time series. This particular algorithm selects the most representative value as the sample which is the closest to the temporal average value estimated over the compositing period. In practice, statistics are performed on one single product, *e.g.*, the FAPAR, in order to identify, within the compositing period, the date which best represents the state of the medium.

2.2 Data products characteristics

Most, if not all, time series of surface products estimated from space borne measurements suffer from intermittency at various frequencies depending, for instance, on the width of the instrument swath, the relative geometry of illumination and observation, the cloud cover and the aerosol load, among other undesirable effects. In the spatial domain, the high-frequency products are thus characterized by low geographical coverage and in the temporal domain, the analysis of the time series is rendered difficult by the absence of product information at irregular intervals.

3 Algorithm description

The temporal average and corresponding average deviation of the product values, $\mathcal{S}$, over the $\mathcal{N}$-day period are first estimated:

$$\begin{aligned} \overline{\mathcal{S}} &= \frac{1}{T}\sum_{t=1}^{T}\mathcal{S}(t) \\ \Delta_{\mathcal{S}}^{T} &= \frac{1}{T}\sum_{t=1}^{T}|\mathcal{S}(t)-\overline{\mathcal{S}}| \end{aligned} \tag{1}$$

where T is the number of valid clear sky values, *i.e.*, the identification number (ID) is equal to 0 (see table1) during the compositing period of $\mathcal{N}$ days . $\overline{\mathcal{S}}$ is the temporal average index value and $\Delta_{\mathcal{S}}^{T}$ is the average deviation of the distribution. The value selected as the most representative for the given $\mathcal{N}$-day period is the actual $\hat{\mathcal{S}}$ value which minimizes the quantity $|\mathcal{S}(t) - \overline{\mathcal{S}}|$.

In order to avoid biasing the results by probable outliers in the time series, this procedure is applied twice sequentially and the $\mathcal{S}$(t) values which are outside the range $\overline{\mathcal{S}} \pm \Delta_{\mathcal{S}}^{T}$ are rejected after the first iteration.

This procedure thus generates maps of geophysical products for every $\mathcal{N}$-day period, where each individual value represents the actual measurement or product for the day considered the most representative of that period. The geometry of illumination and observation for the particular day selected is save as part of the final product, which is thus fully documented and traceable.

3.1 Practical considerations

For all practical purposes, it is appropriate to label each pixel in the intantaneous product file in order to optimize the various steps of the processing to be achieved over various media. Table 1 taken from Gobron et al. (2001) provides an example of the spectral tests that can be applied and the associated categories for discriminating the major geophysical systems (also identified with an identification number), namely clouds, bright surfaces, vegetated surfaces and water bodies. In the data product, the various identification numbers correspond to a set of flag values.

3.1.1 Quality control and diagnostics

3.1.2 Output

The output generated by this time composite algorithm consists of one single value for the product $\hat{\mathcal{S}}$. It also includes, for the period considered the most representative day of that period, the associated rectified red and near-infrared reflectances, the spectral BRF values estimated at the top of the atmosphere as well as the geometry of illumination and observation. In addition, some simple statistical indicators such as the average deviation of the $\hat{\mathcal{S}}$ values over the $\mathcal{N}$-day period are reported for each pixel.

If the ID number (see table1) is equal to 0, the composited $\hat{\mathcal{S}}$ value is valid and reported in the range 0 to 1.0. This situation occurs when at least one value was found valid over the compositing period.

If the ID number is equal either to 4 or 6, the composited $\hat{\mathcal{S}}$ value is valid and reported equal to 0. This situation occurs when at least one daily value was found valid over the compositing period.

If the ID number is equal to 7, the composited $\hat{\mathcal{S}}$ value is valid and reported equal to 1. This situation occurs when at least one daily value was found valid over the compositing period.

Otherwise, the composited $\hat{\mathcal{S}}$ value is equal to its error value and the ID number is set at 1, 2, 3 or 5 as appropriate. This situation occurs when no retrieval has been found valid over the compositing period according to the values of the daily ID number.

Table 1: Pixel labelling criteria

Identification number (ID)	**Spectral tests**	**Associated categories**
0	$0 < \rho_{BLU} < 0.3$ and $0 < \rho_{RED} < 0.5$ and $0 < \rho_{NIR} < 0.7$ and $0 < \rho_{BLU} \leq \rho_{NIR}$ and $\rho_{NIR} \geq 1.25\,\rho_{RED}$	vegetated surface
1	$\rho_{BLU} \leq 0$ or $\rho_{RED} \leq 0$ or $\rho_{NIR} \leq 0$	bad data
2	$\rho_{BLU} \geq 0.3$ or $\rho_{RED} \geq 0.5$ or $\rho_{NIR} \geq 0.7$	cloud, snow and ice
3	$0 < \rho_{BLU} < 0.3$ and $0 < \rho_{RED} < 0.5$ and $0 < \rho_{NIR} < 0.7$ and $\rho_{BLU} > \rho_{NIR}$	water body, deep shadow and others
4	$0 < \rho_{BLU} < 0.3$ and $0 < \rho_{RED} < 0.5$ and $0 < \rho_{NIR} < 0.7$ and $0 < \rho_{BLU} \leq \rho_{NIR}$ and $1.25\,\rho_{RED} > \rho_{NIR}$	bright surface
5	$\rho^{\dagger}_{RRED} < 0$ or $\rho^{\ddagger}_{RNIR} < 0$	undefined
6	$VI < 0$	no vegetation
7	$VI > 1$	vegetation (out of bounds)

† Rectified red reflectance
‡ Rectified near-infrared reflectance

In the specific case where all daily values of the $\hat{\mathcal{S}}$ over the compositing period are equal to 0, the reported output field corresponds to the values for the earliest occurrence of the lowest identification number found.

4 Assumptions and limitations

4.1 Assumptions

The time composite algorithm assumes that a representative value of the $\mathcal{S}$ product does exist during the time composite period. The quality of the output decreases with an increasing the signal variability.

4.2 Limitations

The number of valid $\mathcal{S}(\mathrm{t})$ values in the time series considered for the compositing period must be large enough to ensure that the statistics are significant. In the extreme case, where only one single $\mathcal{S}(\mathrm{t})$ value is available over the $\mathcal{N}$-day period, this value is, by default, taken as the output. If only two $\mathcal{S}(\mathrm{t})$ values are available a choice has to be made *a priori*. In the case of the FAPAR product, it is recommended to select the largest FAPAR value.

5 Algorithm requirements

The implementation of the proposed algorithm to estimate time composite products requires that time series of $\mathcal{S}(\mathrm{t})$ values are available at an appropriate time step with respect to the length of the compositing period.

References

Gobron, N., F. Mélin, B. Pinty, M. M. Verstraete, J.-L. Widlowski, and G. Bucini (2001). A global vegetation index for SeaWiFS: Design and applications. In M. Beniston and M. M. Verstraete (Eds.), *Remote Sensing and Climate Modeling: Synergies and Limitations*, pp. 5–21. Dordrecht, The Netherlands: Kluwer Academic Publishers.

Gobron, N., B. Pinty, F. Mélin, M. Taberner, and M. M. Verstraete (2002a). Sea Wide Field-of-View Sensor (SeaWiFS) - An optimized FAPAR algorithm - Theoretical Basis Document. EUR Report No. 20148 EN, Institute for Environment and Sustainability.

Gobron, N., B. Pinty, F. Mélin, M. Taberner, and M. M. Verstraete (2002b). Sea Wide Field-of-View Sensor (SeaWiFS) - Level 2 land surface products - Algorithm Theoretical Basis Document. EUR Report No. 20144 EN, Institute for Environment and Sustainability.

Gobron, N., B. Pinty, M. M. Verstraete, and M. Taberner (2002c). Global Land Imager (GLI) - An optimized FAPAR algorithm - Theoretical Basis Document. EUR Report No. 20147 EN, Institute for Environment and Sustainability.

Gobron, N., B. Pinty, M. M. Verstraete, and M. Taberner (2002a). Medium Resolution Imaging Spectrometer (MERIS) - An optimized FAPAR algorithm - Theoretical Basis Document. EUR Report No. 20149 EN, Institute for Environment and Sustainability.

Gobron, N., B. Pinty, M. M. Verstraete, and M. Taberner (2002b). VEGETATION - An optimized FAPAR algorithm - Theoretical Basis Document. EUR Report No. 20146 EN, Institute for Environment and Sustainability.

Goel, N. S. and W. Qin (1994). Influences of canopy architecture on relationships between various vegetation indices and LAI and FPAR: A computer simulation. *Remote Sensing Reviews 10*, 309–347.

Holben, B. N. (1986). Characteristics of maximum-value composite images from temporal AVHRR data. *International Journal of Remote Sensing 7*, 1417–1434.

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment 25*, 295–309.

Kaufman, Y. J. and D. Tanré (1992). Atmospherically Resistant Vegetation Index (ARVI) for EOS-MODIS. *IEEE Transactions on Geoscience and Remote Sensing 30*, 261–270.

Leprieur, C., M. M. Verstraete, and B. Pinty (1994). Evaluation of the performance of various vegetation indices to retrieve vegetation cover from AVHRR data. *Remote Sensing Reviews 10*, 265–284.

Meyer, D., M. M. Verstraete, and B. Pinty (1995). The effect of surface anisotropy and viewing geometry on the estimation of NDVI from AVHRR. *Remote Sensing Reviews 12*, 3–27.

Pinty, B., C. Leprieur, and M. M. Verstraete (1993). Towards a quantitative interpretation of vegetation indices. part 1: Biophysical canopy properties and classical indices. *Remote Sensing Reviews 7*, 127–150.

Pinty, B., F. Roveda, M. M. Verstraete, N. Gobron, Y. Govaerts, J. Martonchik, D. Diner, and R. Kahn (2000). Surface albedo retrieval from METEOSAT - Part 2: Application. *Journal of Geophysical Research 105*, 18113–18134.