The CACAO Method for Smoothing, Gap Filling, and Characterizing Seasonal Anomalies in Satellite Time Series

Aleixandre Verger, Frédéric Baret, Marie Weiss, Sivasathivel Kandasamy, *Member, IEEE*, and Eric Vermote

***Abstract*—Consistent, continuous, and long time series of global biophysical variables derived from satellite data are required for global change research. A novel climatology fitting approach called CACAO (Consistent Adjustment of the Climatology to Actual Observations) is proposed to reduce noise and fill gaps in time series by scaling and shifting the seasonal climatological patterns to the actual observations. The shift and scale CACAO parameters adjusted for each season allow quantifying shifts in the timing of seasonal phenology and inter-annual variations in magnitude as compared to the average climatology. CACAO was assessed first over simulated daily Leaf Area Index (LAI) time series with varying fractions of missing data and noise. Then, performances were analyzed over actual satellite LAI products derived from AVHRR Long-Term Data Record for the 1981–2000 period over the BELMANIP2 globally representative sample of sites. Comparison with two widely used temporal filtering methods—the asymmetric Gaussian (AG) model and the Savitzky-Golay (SG) filter as implemented in TIMESAT—revealed that CACAO achieved better performances for smoothing AVHRR time series characterized by high level of noise and frequent missing observations. The resulting smoothed time series captures well the vegetation dynamics and shows no gaps as compared to the 50–60% of still missing data after AG or SG reconstructions. Results of simulation experiments as well as confrontation with actual AVHRR time series indicate that the proposed CACAO method is more robust to noise and missing data than AG and SG methods for phenology extraction.**

***Index Terms*—Advanced Very High Resolution Radiometer (AVHRR), climatology fitting, gap filling, inter-annual anomalies, leaf area index (LAI), phenology, temporal smoothing.**

I. Introduction

Leaf area index (LAI) is recognized as an Essential Climate Variable [44] that plays a key role in a number of processes [12]. Global LAI products are routinely produced from various moderate spatial resolution sensors such as VEGETATION [3], [6], Moderate Imaging Spectroradiometer (MODIS) [28], or the Advanced Very High Resolution Radiometer (AVHRR) [17]. However, the current LAI products are spatially and temporally discontinuous mainly due to cloud occurrence, residual atmospheric or directional effects, snow cover, retrieval algorithm failure or sensor problems which limit their use for the monitoring of vegetation dynamics. To better describe and understand vegetation dynamics in response to climate fluctuations and trends (e.g. temperature, rainfall, solar radiation) and/or anthropogenic forcing (e.g., ground water extraction, farming decisions, change in land use) [9], [10], [29], [31], consistent and continuous long time series of global LAI products are thus required. Variations in magnitude and shifts in the timing of vegetation phenology are key indicators for global change issues [41]. However, extracting the associated metrics to quantify trends, anomalies, or changes from the satellite time series is not straightforward: the noise in the data and missing observations may induce significant uncertainties in the estimation of these metrics [23]. The literature shows a broad variety of strategies designed to reduce noise and fill gaps in time series including the widely used asymmetric Gaussian (AG) [23], Savitzky-Golay (SG) filter [13], [37], double logistic function [20], [25], Fourier analysis [9], and wavelet decomposition [33]; as well as to extract phenological metrics and monitor vegetation dynamics based on thresholds [29], [42], moving averages [32], empirical equations [27], conceptual-mathematical phenology models [15], first derivatives and piecewise logistic functions [43], spectral-frequency decomposition techniques [9], [33], [34], and curve fitting [23], [25]. The choice of the smoothing gap filling or compositing method may have a large impact on the accuracy of the extraction of phenology indicators since their ability to preserve the integrity (magnitude and shape) of the overall time series may vary [1], [21]. Recently, [41] compared several methods for extracting phenological timing and found some large discrepancies, up to ± 60 days in the detection of start of the season. Most of these time series analysis have been carried out using the normalized difference vegetation index (NDVI) which is a proxy of vegetation biophysical variables. However, LAI offers the advantage to be more sensitive to the larger vegetation amount as compared to NDVI or other vegetation characteristics such as the Fraction of Absorbed Photosynthetically Active Radiation [2], [30].

A novel approach is proposed here to smooth and fill gaps in LAI long time series derived from AVHRR observations at 0.05° spatial resolution [39]. The method is based on the typical

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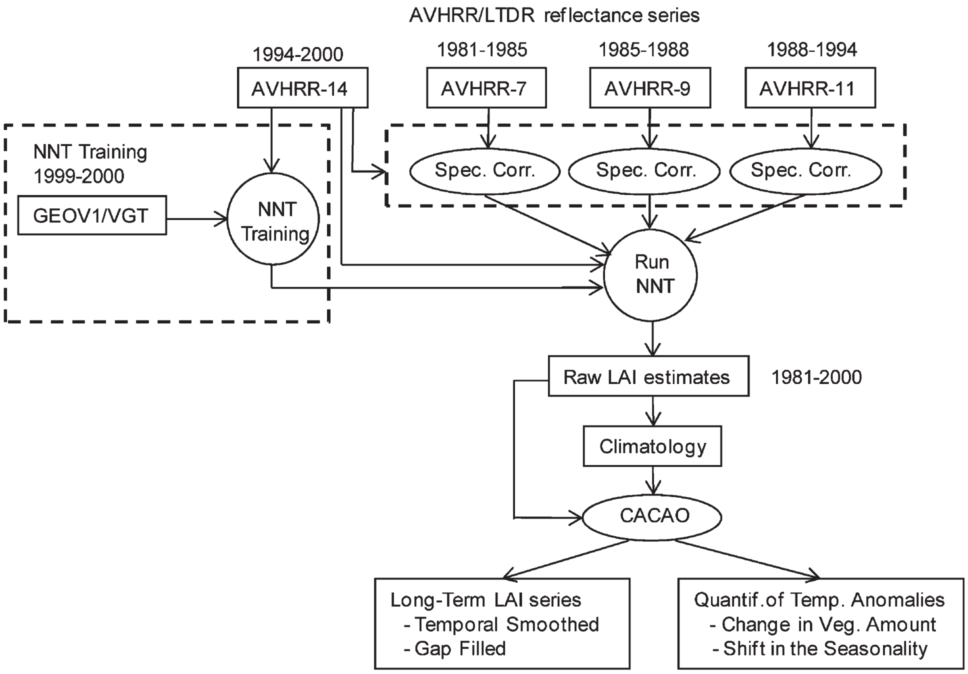

Fig. 1. Flow chart of the algorithm for deriving consistent and continuous long-term daily LAI data set as well as quantifying temporal anomalies.

seasonal pattern of each pixel, i.e., the pixel phenology model. It is used as a background information to fill gaps and smooth the time series of daily LAI estimates derived by learning GEOV1 LAI products [5]. The phenology model is based on the climatology of LAI values computed as the average value for a given date in the year across all years of the time series. For each pixel, the corresponding phenology model is adjusted to each season of the time series by shifting its time reference and scaling its magnitude. As opposed to several other smoothing and gap filling methods listed previously, the phenology model derives only from the satellite observations themselves. The resulting smoothed and gap filled time series provides the shift and scale parameters associated to each season as subproducts. They can be used to quantify inter-annual deviations in vegetation status from the average pattern often called "anomalies." Because the same climatological phenology model is used across all the years, the method applies strictly to quantify phenological changes, i.e., change in the parameters of the phenology model, rather than a change of the phenology model [16] corresponding to a change generally associated to abrupt disturbances [26], [35].

This study presents the principles of the proposed method. It is then evaluated against other methods, focusing on the capacity to smooth the daily LAI estimates and to fill the gaps. Finally, the interest of the resulting shift and scale parameters to quantify anomalies is evaluated.

II. Data and Methods

Global long-term LAI time series derived from AVHRR in the 1981–2000 period were used to assess the proposed approach under a variety of conditions. The analysis was conducted over the 445 BELMANIP2 (BEnchmark Land Multisite Analysis and Inter-comparison of Products) sites that are supposed to represent the possible range of surface types and conditions over the Earth [Fig. 5(b)] [4]. The LAI data set is first presented, followed by a description of the main steps for the implementation of the proposed method (Fig. 1) as well as the AG and SG companion methods from TIMESAT. Then, the simulation experiment designed for assessing the methods under varying fraction of missing data and noise level and the metrics are described.

A. Generation of a Long-Term LAI Data set

The derivation of the long-term daily LAI data set is based on the previous work of [36] demonstrating that neural networks could be trained to consistently estimate a given product from the reflectance measured by another sensor providing that a strong link exists between the inputs (radiometric signal) and outputs (the products). This principle is applied here to mimic GEOV1/VGT dekadal LAI product [6] from historical AVHRR archive data.

AVHRR Long-Term Data Record (LTDR, Version 3) [45] provides global coverage at 0.05° (5.6 km at equator) sampling interval in a latitude/longitude climate modeling grid and at a daily temporal step for the 1981–2000 period. LTDR top of the canopy normalized reflectances (nadir, sun at 45°) result from the reprocessing of Global Area Coverage data set by applying the preprocessing improvements identified in the AVHRR Pathfinder II and MODIS projects for radiometric calibration, geometric correction, cloud screening, and corrections of the atmospheric and directional effects [38], [39].

GEOV1/VGT LAI product, available at [46], provides global coverage for the period 1999–2010 at 1 km spatial resolution and dekadal time step [6]. Recent validation studies showed the GEOV1 products to outperform the currently available products both in terms of accuracy and precision [11].

A back-propagation neural network with a relatively simple architecture made of one hidden layer of five tangent sigmoid neurons and one output layer with one linear neuron was considered based on the previous findings of [36]. Red and

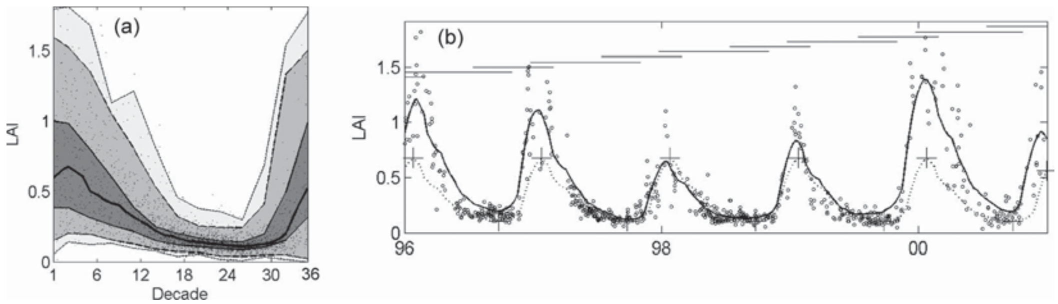

Fig. 2. Illustration of CACAO implementation over the cropland site #128 (Fig. 5(b); Lat = −23.48°, Lon = 28.20°). (a) Climatology computation. Dots indicate the accumulated LAI daily data over the period 1981–2000. The bold line corresponds to the climatology computed as the median of inter-annual values over a 30-days compositing window at a dekadal step. The several gray values correspond to 50% (dark gray), 95% (medium gray) and 99% (light gray) of the population of values for a given date. (b) CACAO fitting for the period 1996–2000. Circles correspond to raw LAI data. The dotted line corresponds to the climatology and the continuous line corresponds to the CACAO time series resulting from adjusting the climatology to the data at a daily step. The plus symbols indicate the position of the minima and maxima in the climatology and the segments indicate the duration of the sub-seasons for the fitting.

near-infrared AVHRR LTDR surface reflectance normalized at nadir viewing for a 45° sun zenith angle were used as inputs. The network was trained over the BELMANIP2 sites in the 1999–2000 period in which LTDR and GEOV1 products are coexisting. Differences in spatial resolution between AVHRR LTDR (0.05°) and GEOV1/VGT (1/112°) products were taken into account by averaging the GEOV1/VGT products over 3×3 km^2. Residual differences due to spatial resolution and geometry uncertainties are expected to be small because the BELMANIP2 sites were selected to be relatively homogeneous at the medium spatial resolution [4]. The dekadal GEOV1/VGT product was linearly interpolated at the dates for which LTDRV3 reflectances were available since the objective is to provide daily LAI products. This interpolation benefits from the smooth character of GEOV1/VGT temporal profiles [11]. To account for possible spectral sensitivity differences between the several AHVRR-XX sensors available over the 1981–1998 period and AVHRR-14 used in 1999–2000 for the neural network training, AVHRR-XX reflectances in the red and near infrared were corrected to mimic the AVHRR-14 ones. The correction was achieved by computing a scaling factor between the reflectance of AVHRR-XX with that of AVHRR-14. The correction factor was adjusted over radiative transfer model simulations using the PROSAIL radiative transfer model [22] and the specific spectral responses of the several AVHRR-XX sensors. A flowchart of the retrieval algorithm is presented in Fig. 1. Further information about the generation of the LAI data set is provided in [7].

B. Consistent Adjustment of the Climatology to Actual Observations

A climatology defined as the inter-annual median of the daily products available within a 30-days compositing window (±15 days) was generated at a dekadal temporal step (a 10-days period; there are thus 36 dekads over one year) and at the pixel scale (0.05° spatial resolution). It corresponds to the phenology model used later for smoothing and gap filling. The climatology value was computed for each dekad if a minimum of five observations over the 30-days compositing window exist. Climatology computation is illustrated in Fig. 2(a). The whole period (1981–2000) was used to minimize the probability of finding a gap. The resulting dekadal pixel phenology model was generally showing very smooth profiles [Fig. 2(a)]. It was thus linearly interpolated to provide a daily climatology, LAI^{CLIM}, consistent with the daily time step of the daily LAI products derived from AVHRR observations.

A Consistent Adjustment of the Climatology to Actual Observations (CACAO) was then performed by shifting (*shift*) and scaling (*scale*) the phenology model in order to minimize the root mean square error (*RMSE*), between the actual daily LAI estimates, $LAI(t)$, and the CACAO estimates $\widehat{LAI}^{CACAO} = scale.LAI^{CLIM}(t + shift)$ over portions of the seasonal cycle called “sub-seasons”:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(LAI(t_i) - \widehat{LAI}^{CACAO}(t_i)\right)^2} \qquad (1)$$

where t is the time in days and n is the number of available dates of observations during the sub-season. If the actual observations follow the phenology model, $LAI^{CLIM}(t)$, the scale factor and the temporal shift parameter are by definition $scale = 1$ and $shift = 0$. The cost function was evaluated for 121 values of the shift ($-60\ days < shift < 60\ days$ with steps of 1 day), the *scale* being adjusted using a linear regression with no intercept. However, difficulties to fit the *shift* parameter are expected when a small number of observations are available in the sub-season or if the data present a limited seasonality. Therefore, CACAO is applied if a minimum of $n = 10$ observations representing at least 30% of the LAI climatology amplitude (difference between minima and maxima in the climatology values) within the sub-season is available. Otherwise, the climatology is used as a backup solution.

A sub-season is defined as the period between two consecutive minimum and maximum in the LAI climatology. To allow more robust fitting by providing better handle on temporal features and smoother transitions between sub-seasons, the sub-season period used to adjust the phenology model is slightly extended. This extended period added before (respectively, after) the sub-season should contain either 30% of the season amplitude or 30% of the period length (in days) of the previous (resp. next) sub-season. Over the transition periods where CACAO fitting extended sub-seasons overlap, a weighted average of $\widehat{LAI}^{CACAO}$ values is finally computed to get continuous and smooth temporal profiles. CACAO fitting process is illustrated in Fig. 2(b) with each sub-season used to adjust the phenology model displayed.

Similar to other methods [19], [33] based on the fitting of a phenology model, CACAO implicitly assumes that the vegetation species composition and state did not dramatically change so that a single phenology model can be used over the whole 20-years period. CACAO is therefore expected to encounter difficulties in case of disturbances such as landcover or land-use change, fire or flood events covering a large fraction of the pixel. However, the sub-season fitting approach provides some capacity to adapt to reasonable deviations from the original shape of the phenology model. Further, disturbances occur mainly at finer spatial scale as compared to the 0.05° coarse spatial resolution considered here. They are therefore expected to impact only occasionally the shape of the phenology model. Difficulties are also expected when artifacts in phenology model may appear due to a small number and/or very noisy observations are observed during the period used to compute the climatology. However, the daily temporal sampling of AVHRR observations, the 30-days compositing window, and the 20-years period used to compute the climatology decrease the probability to get strong artifacts in the phenology model. Nevertheless, the 30-days compositing window and the averaging over the 20 years may flatten particular features in the phenology model such as rapid LAI changes shifted significantly across years and sub-seasonal anomalies mostly linked with unusual temperature or rainfall events. CACAO further assumes that the actual LAI as a function of time is only proportional to the shifted climatological LAI value without considering any possible LAI offset. This approximation is reasonable since the minimum LAI values are generally relatively small and stable in absolute term. In all these situations, the *RMSE* value will provide a quantitative quality assessment indicator of the consistency between the phenology model and actual daily observations. Finally, although CACAO is able to provide realistic temporal profiles in case of marginal seasonality observed over bare areas or evergreen forests, it is expected to be more difficult to fit the shift parameter in a robust way. Therefore, the time shift parameter should not be interpreted in such conditions.

C. AG and SG TIMESAT Methods

For comparison purposes, CACAO was compared with two widely used temporal filtering methods: AG and adaptive SG as implemented in the TIMESAT toolbox for analyzing time series of satellite observations [24], [47]. Double logistic function produces very similar results as AG while being more sensitive to discontinuities in the data in agreement with [18]. TIMESAT has been successfully applied to extract phenology from AVHRR time series and was found to outperform Fourier decomposition methods that were experiencing difficulties in presence of noise and missing data such as in the AVHRR series [23]. The adaptive SG-filtering method uses local second-order polynomial functions in fitting three observations at each side of the date being processed. AG method uses a Gaussian function that is fitted to data around maxima and minima in the time series.

AG and SG methods failed in processing a significant part of the daily AVHRR time series characterized by many gaps. Indeed, data cannot be processed if there is a missing time period longer than 0.2 years or when more than 25% of data are missing over the entire time series. To use AG and SG over AVHRR time series characterized by more than 70% of missing data (Section III-A3), a simple gap filling method was applied: first, an iterative linear interpolation was used to fill gaps smaller than 120 days [37]; second, a temporal compositing was applied at 10-day step through a Gaussian function with a 30-day compositing period.

In addition to the time series reconstructions, TIMESAT toolbox allows to compute some phenological metrics including the season amplitude (i.e., difference between the maximal value and the base level), the start of season (hereafter referred as SoS) and the end of season (hereafter referred as EoS). The time of the SoS (EoS) is defined as the time for which the left (right) edge reached 20% of the seasonal amplitude measured from the left (right) minimum level.

D. Simulation Experiment

A simulation experiment was conducted to evaluate the performances of the several methods in presence of noise and missing observations as already proposed by [34], [37], [40]. For this purpose, the complete and smooth time series resulting from the median of CACAO, AG, and SG reconstructed profiles for site #338 showing a double season (Fig. 4) was first considered as a reference, LAI_{ref}. Note that only few observations are missing over site #338, resulting in a relatively good consistency between the three methods investigated. Then, missing observations were randomly distributed, and several levels of white noise were introduced in the reference LAI time series to simulate the actual daily LAI data, LAI_{day}. The noise component was generated using a normal distribution $\aleph(0, \sigma)$ (mean value equal to 0 and variance, σ^2), i.e., $LAI_{day} = LAI_{ref} + \aleph(0, \sigma)$. The values for the absolute LAI uncertainty used in this study were varying between $\sigma = 0$ and $\sigma = 0.5$ by 0.05 steps. The fraction of missing data was ranging between 0 and 0.85; few tests showed that for fractions of missing data larger than 0.85, all the methods were unreliable and AG and SG failed in most of cases which prevents deriving meaningful statistics. Finally, the CACAO, AG, and SG methods were applied to the simulated time series with variable fraction of missing data and level of uncertainties.

E. Metrics

The reconstructed time series were then compared with the original reference data and the corresponding $RMSE_{ref}$ computed and used as an indicator of performances:

$$RMSE_{ref} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{LAI(t_{\mathrm{i}})} - LAI_{ref}(t_i)\right)^2} \quad (2)$$

where $\widehat{LAI(t)}$ is the estimated LAI value at date t, $LAI_{ref}(t)$ is the reference LAI data, and n is the number of dates in the time series for which the reconstructions of the three compared methods are available. In order to obtain representative values, the $RMSE_{ref}$ was derived from 50 iterations for each level of noise and gap fraction. The closeness to the actual daily raw LAI data is also evaluated using $RMSE_{raw}$

$$RMSE_{raw} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{LAI(t_{\mathrm{i}})} - LAI_{raw}(t_i)\right)^2}. \quad (3)$$

Similar metrics were used for the evaluation of the phenological parameters (P) extracted from CACAO and TIMESAT methods. $RMSE^P_{ref}$ is defined as

$$RMSE^P_{ref} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{P(t_\mathrm{i})} - P_{ref}(t_i)\right)^2} \tag{4}$$

where $\widehat{P(t)}$ is the estimated phenological P parameter at date t, $P_{ref}(t)$ is the corresponding P parameter as computed from the reference time series, and n is the number of available dates used in the comparison. When the methods are applied to actual AVHRR time series, a reference is not available, and the deviation of P parameters from their mean value (the climatological one) is considered in this case for computing the $RMSE^P_{raw}$

$$RMSE^P_{raw} = \sqrt{\frac{1}{m}\sum_{j=1}^{m}\frac{1}{n}\sum_{i=1}^{n}\left(\widehat{P_\mathrm{j}(t_\mathrm{i})} - \overline{P}_\mathrm{j}\right)^2} \tag{5}$$

where $P_\mathrm{j}(t_\mathrm{i})$ is the P value at date t for the time series j, $\overline{P}_\mathrm{j}$ is the mean value of P along the time series j, n is the number of dates corresponding to the phenological P stage in the time series, and m the number of time series.

III. Results

The performances of the CACAO method was evaluated against TIMESAT AG and SG methods for A) improving the consistency and continuity of the time series and B) for the characterization of inter-annual anomalies through time shifts of phenological stages and magnitude (scale) of LAI values. The assessment was performed over the BELMANIP2 sites across the main biome classes based on the GLOBCOVER land cover map [8].

A. Performances of CACAO for Improving the Consistency and Continuity of Time Series

The theoretical performances of CACAO, AG, and SG are first presented. Then, typical temporal profiles are inspected. Finally, the continuity and consistency are evaluated over the entire BELMANIP2 sites.

1) Theoretical Performances as a Function of Fraction of Missing Data and Daily LAI Uncertainties: The theoretical performances were evaluated over the simulated data using the $RMSE_{ref}$ value computed with the reference data. Results show that for low to medium values of fraction of missing data, the performances are mainly depending on the daily LAI uncertainties [Fig. 3(a)]. For the larger fraction of missing data, CACAO performances are strongly degrading with the fraction of missing data and the daily LAI uncertainties.

The performances of SG and AG methods as a function of the fraction of missing data and the daily LAI uncertainties show similar patterns as those of CACAO (figures not shown for the sake of brevity). However, Fig. 3(b) demonstrates that the CACAO method outperforms AG and SG methods in all the situations, particularly for the higher levels of the fraction of missing data and daily LAI uncertainties. AG gets slightly lower $RMSE_{ref}$ values as compared to SG.

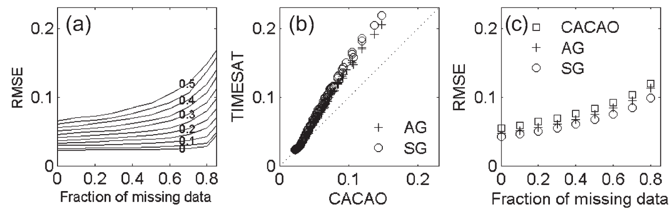

Fig. 3. (a) Evaluation of theoretical performances of CACAO in terms of $RMSE_{ref}$ as a function of the fraction of missing data varying between 0 and 0.85 and the σ noise level $(LAI_{noisy} = LAI + \aleph(0,\sigma))$ varying between 0 and 0.5. (b) Comparison of the $RMSE_{ref}$ of the two TIMESAT methods with the $RMSE_{ref}$ of CACAO as evaluated over the reference data. (c) $RMSE_{raw}$ of CACAO, AG, and SG over the raw data as a function of the fraction of missing data.

Although the CACAO reconstructed LAI time series is the closest to the reference LAI values, it is the one that allows more departure from actual daily LAI values (higher $RMSE_{raw}$ values), particularly when the daily LAI data are contaminated with large uncertainties [Fig. 3(c)]. The use of the climatology as background information provides robustness gap filling and smoothing processes.

2) Inspection of Typical Temporal Profiles: The main features associated to the temporal consistency of CACAO, AG and SG are illustrated over a selection of six sites representing different conditions with the location indicated in Fig. 5(b). The sites were also selected so that AG and SG methods were not failing. In most of the cases, a good agreement is found between the three methods that similarly fit the raw daily LAI data when few observations are missing (Fig. 4, site #338). However, the reliability of the retrieved temporal profile depends on the level of noise and the presence of gaps in the data as demonstrated earlier with the simulated cases. Noisy daily LAI data are partially filtered out for AG and SG methods as implemented in TIMESAT where single spikes are removed based on the distance to neighbor data. This approach may be useful to eliminate possible high temporal frequency residual artifacts but appears insufficient to process AVHRR series in case of significant uncertainty associated to the daily LAI data (e.g., Fig. 4, site #436) and repetitive occurrence of consecutive outliers (year 1988 in site #325). SG seems to be the most sensitive to accidents in the data: Fig. 4, site #436 which is expected having a minimum seasonality; site #395, winter time for years 1982, 1984, and 1990; or site #325, year 1990 during the maximum development of vegetation. Conversely, AG reduces most of the residual noise. The assumption made in AG about the shape of the seasonal phenology development helps reducing the effect of noise in the data. However, AG may present some limitations to reproduce abrupt variations in LAI, related to the emergence, greening up, wilting, or harvesting of the crops within a short growing season or secondary sub-seasons as for site #69 in Fig. 4. In contrast, SG is not explicitly tied to a specific shape regarding phenology development and thus better adapt to local characteristics of the observed signal (e.g., double seasonality in site #69). Similar to AG, CACAO appears to be robust to noise. However, while the phenological shape function is fixed in AG, CACAO is able to adapt it from pixel to pixel thanks to the corresponding phenology model derived from the climatology, which provides additional flexibility. Nevertheless, some problems still remain in the CACAO approach: scaling and shifting the climatology

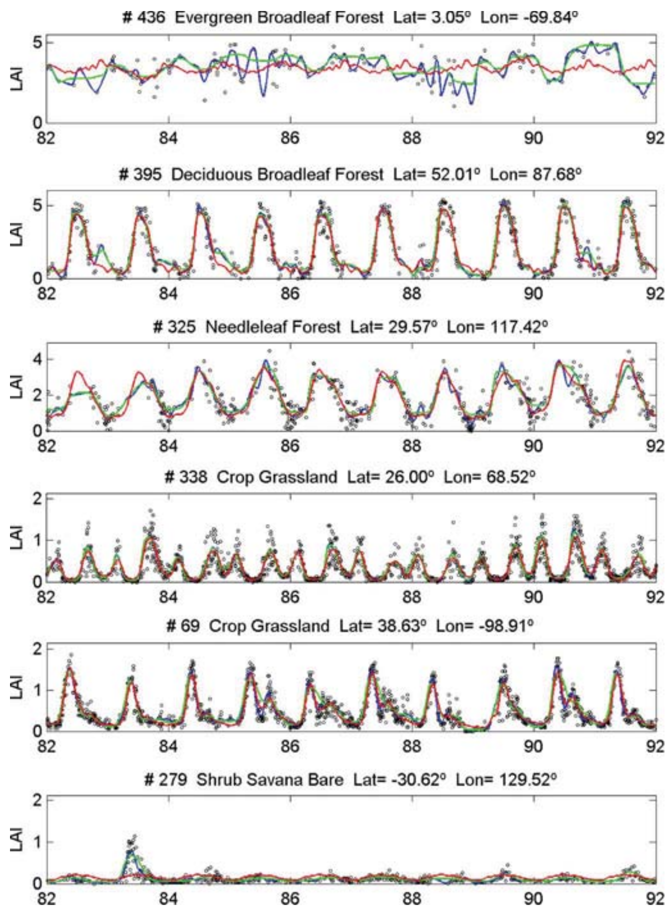

Fig. 4. Temporal profiles of raw LAI data (black circles), CACAO (red line), AG (green line), and SG (blue line) LAI reconstructions for six BELMANIP2 sites from 1982 to 1992. The # number of each site refers to Fig. 5(b). The GLOBCOVER biome class [8] and the latitude and longitude are also indicated. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

may be inappropriate to depict local rapid changes (e.g., local minima in site #69) or sub-seasons that strongly differ from the average seasonality (e.g., Fig. 4, site #279, year 1983).

The temporal continuity in the AVHRR data is generally poor in the equator (e.g., Fig. 4, sites #436) due to the persistence of clouds and at high latitudes in winter time (e.g., Fig. 4, site #395) mainly due to snow and cloud cover as well as poor illumination conditions due to large sun zenith angles. CACAO approach appears very useful to fill gaps in the time series and may overcome some of the limitations of AG and SG to deal with gaps (e.g., Fig. 4, site #325, years 1982–1983). Note that when there is no enough data over the entire sub-season for fitting the model, the climatology is assumed as the most probable solution (e.g., Fig. 4, site #436, years 1982, 1987–1989, 1990–1991; site #325, year 1983) which may be not realistic for very anomalous years.

3) Continuity of the Time Series: The total fraction of missing AVHRR daily observations is around 73% over the 445 BELMANIP2 sites in the period 1981–2000. It mainly occurs along the equatorial zone because of high probability of cloud coverage and in winter (respectively summer) in the northern (respectively southern) higher latitudes because of the poor illumination conditions [Fig. 5(a)]. This demonstrates that the continuity of time series of the raw AVHRR observations may be very poor in many situations. The CACAO method allows filling all the missing data, even when there is not enough data in a sub-season to achieve a good fit of the phenology model. In this case, the phenology model derived from the climatology is used. This happens in about 23% of cases $(\text{pixels} \times \text{dates})$. Note that there was always enough data to compute the climatology of each of the 445 BELMANIP2 sites over the 20-years period and the 30-days local compositing window. Cases with missing climatology are therefore expected to be very limited over the globe.

Conversely, AG and SG methods were failing over, respectively, 238 (53% of the sites) and 209 (47%) sites where there were not enough high-quality observations to fit a curve over a given local time period. These sites were mostly located at the equator and at high latitudes where there are long periods with missing data [black filled circles in Fig. 5(b)]. AG fails in more cases than SG because AG requires a minimal seasonality in the time series to fit the AG model: 29 desert sites are not processed [gray-filled circles in Fig. 5(b)].

4) Temporal Consistency: Because there are generally no reference LAI values for most of the sites, the temporal consistency is evaluated based on the closeness to actual daily data $(RMSE_{raw})$ and the smoothness of the temporal profiles. The spatio-temporal distribution of $RMSE_{raw}$ [Fig. 6(a)] shows obvious patterns, with higher uncertainties in winter for the higher northern latitudes and around the equator. The higher $RMSE_{raw}$ values correspond to the more difficult observational conditions over regions/periods with permanent snow and cloud cover [cf. Fig. 5(a) and Fig. 6(a)]. The relationship between closeness to daily observations $(RMSE_{raw})$ shows that all the three methods agree well for fraction of missing data lower than 0.5 [Fig. 6(b)]. For the larger fraction of missing data, CACAO and AG show an increasing departure from the daily observations as compared to SG. This was already noticed with the simulation experiment where CACAO showed larger $RMSE_{raw}$ as compared to AG and SG [Fig. 3(c)], but smaller $RMSE_{ref}$ [Fig. 3(b)], particularly in case of high fraction of missing data and high level of uncertainties associated to the daily LAI data. The smoothness of the temporal profiles derived from CACAO confirms the good temporal consistency of the CACAO method.

Smooth temporal profiles are expected since leaf area dynamics results from incremental bio-physical processes except under sudden disturbance. The smoothness level of LAI temporal series was evaluated using the difference, δLAI between $LAI(t)$ product value at date t and the mean value between the two bracketing dates: $\delta LAI = 1/2(LAI(t+\delta t) + LAI(t-\delta t)) - LAI(t)$, where δt is the 10-days temporal sampling interval ([37]). Difference δLAI is computed only if the two bracketing LAI values at $(t-\delta t)$ and $(t+\delta t)$ exist. The smoother the temporal evolution, the smaller the δLAI difference should be. The histogram of δLAI over the BELMANIP2 sites in the 1981–2000 period (Fig. 7) shows the effectiveness of the three methods to smooth the AVHRR raw data. SG method appears the most sensitive to noise in the data conversely to AG method that provides the smoothest profiles since it benefits from fitting data to a single and smooth phenology model. CACAO constitutes an intermediate solution between SG and AG in terms of smoothness. It is very robust to accidents in the data since the climatology plays a major

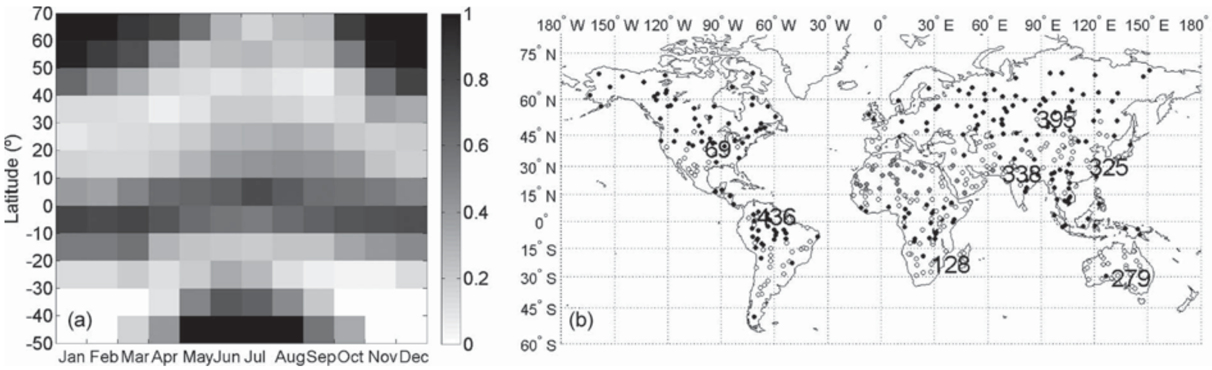

Fig. 5. (a) Fraction of missing data for AVHRR daily products as a function of the latitude and the date of acquisition in $10^\circ \times$ 1-month cells. Evaluation over the BELMANIP2 sites during the 1981–2000 period. (b) Location of the BELMANIP2 sites where (i) CACAO and SG and AG TIMESAT methods successfully processed the AVHRR time series (unfilled circles), (ii) CACAO and SG success and AG fails (desert sites) (gray-filled circles) and (ii) only CACAO success (black filled circles). The numbers refer to the sites in Fig. 2 and Fig. 4.

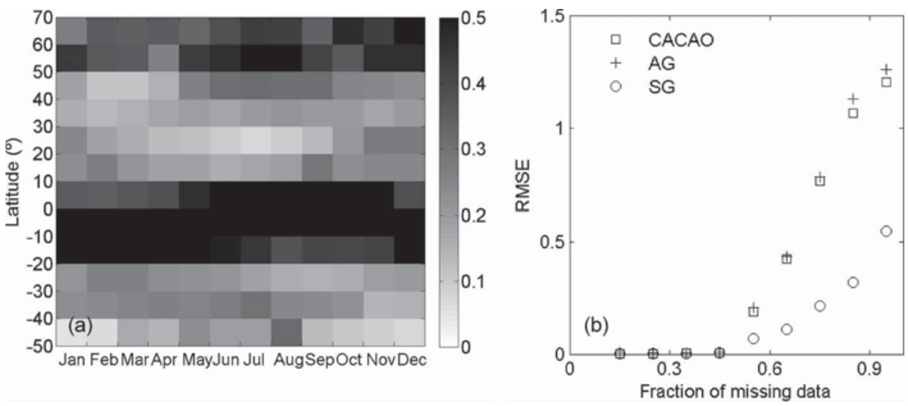

Fig. 6. (a) $RMSE_{raw}$ between CACAO and raw LAI data as a function of the latitude (10° steps) and the date of acquisition (monthly step). (b) $RMSE_{raw}$ of CACAO, AG, and SG over the raw data as a function of the fraction of missing data. Evaluation over the 445 BELMANIP2 sites during the 1981–2000 period.

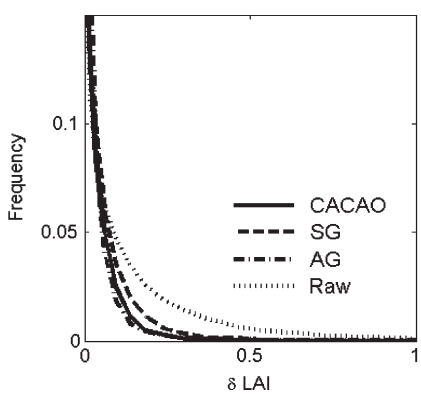

Fig. 7. Histogram of δLAI absolute difference representing temporal smoothness.

regularization role while allowing fitting local variations at the same time.

B. Use of CACAO to Characterize Inter-Annual Anomalies

The estimated shift and scale parameters from CACAO provide indicators of phenological changes. For comparison purposes, the phenological parameters derived from AG and SG as implemented in TIMESAT for each of the full seasons were used. For AG and SG methods, the lag between the time of start or end of each season and the corresponding average date across all seasons was compared with the CACAO shift. The variation of the season amplitude parameter for AG and SG methods was divided by the corresponding average amplitude across all seasons and was compared to the CACAO scale factor.

The simulation experiment was first completed to better assess the theoretical performances of the CACAO, AG, and SG to accurately date the main phenological stages. Then, performances will be analyzed over a larger set of actual sites.

1) Theoretical Performances for Phenology: The $RMSE^P_{ref}$ computed over the simulated data as compared to the reference data was used to score the performances of CACAO, AG, and SG methods. Results (Fig. 8) show that the performances are highly depending on the daily LAI uncertainties and the fraction of missing data with similar tendencies as in Fig. 3(a). The CACAO method outperforms AG and SG methods in all the situations for SoS [Fig. 8(a)] and EoS [Fig. 8(b)]. AG provides lower $RMSE^P_{ref}$ values than SG. Conversely, only small differences are observed between the three methods for the amplitude [Fig. 8(c)].

2) Quantifying Phenological Changes in the Time Series: The comparison of phenological shifts and scales between the three methods as computed over the actual time series across the 445 BELMANIP2 sites shows a generally good agreement between all the methods with unbiased residuals (Fig. 9).

However, the shift and scale parameters derived fromthe CACAO method appear more stable: lower $RMSE^P_{raw}$ values are observed (Fig. 10), quantifying the deviation between each

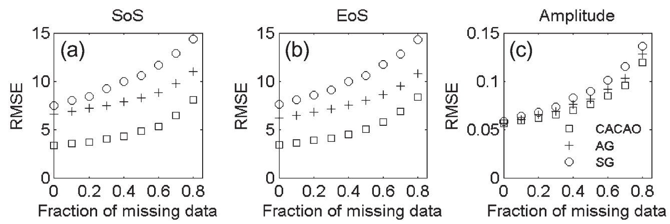

Fig. 8. Theoretical performances $(RMSE_{ref}^{P})$ of the phenology extractions for the (a) start of season (SoS), (b) end of season (EoS), and (c) amplitude of the simulated LAI time series as derived from CACAO, AG, and SG methods as a function of the fraction of missing data.

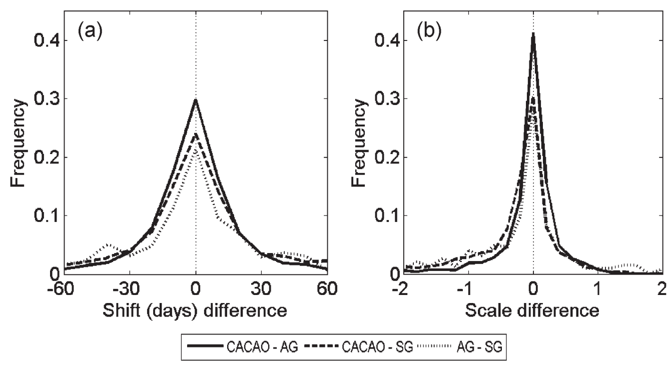

Fig. 9. Histogram of differences of (a) the shift in the start of season (SoS) and end of season (EoS) and (b) the scale factor (variation in seasonal amplitude) representing temporal anomalies of LAI data to the climatological pattern as resulted from CACAO and TIMESAT AG and SG method adjustments over the BELMANIP2 sites for the period 1982–1992.

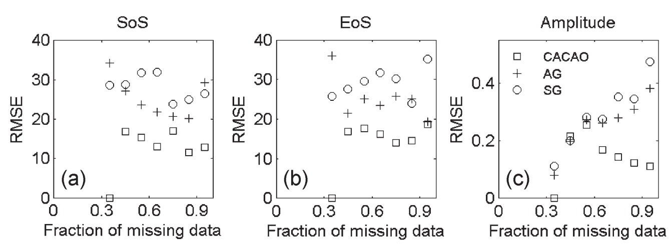

Fig. 10. $RMSE_{raw}^{P}$ of the phenology extractions for the (a) start of season (SoS), (b) end of season (EoS), and (c) amplitude of the actual AVHRR LAI time series as derived from CACAO, AG, and SG methods as a function of the fraction of missing data.

season from the average value across all the seasons. Further, CACAO shift and scales appear only little sensitive to the fraction of missing data (Fig. 10). The same is observed for AG and SG SoS and EoS [Fig. 10(a) and (b)], while the amplitude derived from these two methods appears more sensitive to the fraction of missing data [Fig. 10(c)]. Although these results obtained on actual data do not constitute an undisputable proof of the performances of CACAO for quantifying inter-annual anomalies because of the lack of reference values, they contribute to consolidate the promising theoretical results.

IV. Conclusion

This paper introduces the CACAO method: a new climatological fitting approach for smoothing, gap filling, and quantifying vegetation anomalies in satellite time series. It is based on the fitting of a phenology model. This model is specific to each pixel and is derived from the climatology computed over the time series of the considered pixel. CACAO method appears to be a compromise between very flexible methods such as the adaptive SG filter and methods based on a unique phenology model such as the AG method. The performances of CACAO were evaluated by comparison with the widely used AG and SG methods as implemented in the TIMESAT toolbox. In terms of the required computer resources, CACAO is as demanding as AG, although SG is twice faster.

The CACAO method was first applied to simulated time series of daily LAI estimates as derived from AVHRR observations. This simulation experiment shows a significant improvement in the theoretical performances of LAI reconstructions and phenology extraction for CACAO as compared to SG and AG methods in all the situations, particularly for the higher levels of the fraction of missing data and daily LAI uncertainties.

Results observed over actual AVHRR satellite data showed the potentials of the proposed CACAO method to capture the seasonality in the data while improving consistency and continuity of the time series. CACAO overcomes the difficulties of AG and SG methods to process the irregular nature of the AVHRR time series due to the large fraction of missing data (around 73%) and the high noise level associated. The AG and SG methods failed in processing, respectively, 238 and 209 of 445 BELMANIP2 sites because not enough high quality data was available for fitting the function which resulted, respectively, in 60% and 47% of invalid products. In contrast, the CACAO method allowed filling all the gaps and in particular during long periods of missing data where the climatology computed across the 20-years period of available AVHRR observations was used. The assessment of the temporal consistency and the smoothness of LAI profiles revealed that CACAO constitutes an intermediate solution between AG and SG in terms of robustness and adaptability to local variations.

The scale and shift parameters derived from CACAO allowed the quantification of inter-annual anomalies and showed a relatively good consistency with the seasonality extracted from AG or SG phenological parameters. However, the simulated experiments conducted in this study showed a better accuracy of CACAO for the dating of the start or the end of the season as compared to that derived from AG and SG methods. Nevertheless, further confrontations with climatic variables or phenological models [14] as well as validation with ground-based phenological observations should be conducted. This accuracy assessment should include the spatio-temporal performances of CACAO as compared with other existing methods including Fourier analysis and piecewise decomposition.

However, the main limitation of CACAO reconstruction method is its inability to capture underlying atypical modes of seasonality including rapid natural and human induced disturbances in the LAI time series that strongly differ from the average climatology (e.g., flood or fire events, changes in the land cover). To prevent from such drawback, the resulting fitted climatology can be fused with a product closer to the actual LAI observations as the one resulting from the adaptive SG filtering. This fusion approach should overcome CACAO limitations when enough daily LAI observations are available. It will be implemented in future products to generate continuous long-term Earth System Data Records from remote sensing data collected with several sensors over the past three decades [7]. These algorithms will be adapted to the next generation of sensors such as VIIRS, PROBA-V, and Sentinel 3. These long-term data records and the proposed climatology fitting approach are expected to contribute to identify the trends at the global scale corresponding either to a change (positive or negative) in vegetation amount or in a shift of the seasonality.

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