Robust Identification of Global Greening Phase Patterns from Remote Sensing Vegetation Products

CAROLA DAHLKE, ALEXANDER LOEW, AND CHRISTIAN REICK
Max Planck Institute for Meteorology, Hamburg, Germany

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ABSTRACT

The fraction of absorbed photosynthetically active radiation (fAPAR) is an essential diagnostic variable to investigate the temporal and spatial dynamics of the terrestrial biosphere. The present study provides a new method to assess global vegetation greening phase dynamics, derived from fAPAR time series from four different remote sensing products. A robust algorithm is developed to detect intra-annual greening phase patterns and derive seasonality patterns of vegetation dynamics at the global scale. The comparison of four independent remote sensing datasets shows significantly consistent global spatiotemporal patterns at the 95% confidence level. Regions where the remote sensing datasets show consistent results, as well as regions where at least one of the used remote sensing datasets deviates, can be identified. The derived global greening phase dataset and analysis method provides a solid framework for the evaluation of global vegetation models.

1. Introduction

Vegetation dynamics play a vital role for estimating global carbon fluxes and the interaction of the land surface with the atmosphere. The terrestrial biosphere interacts with global and regional climate. Vegetation–climate feedbacks have been assessed on regional to global scales (e.g., Alessandri and Navarra 2008; Liu et al. 2006). The biotic productivity and exchange between the biosphere and atmosphere influences the seasonal dynamics of plant phenology, which may therefore be used to diagnose the current vegetation response to climate in time and space. Phenological signals such as the onset (“green-wave”; Schwartz 1994, 1998) and the end of vegetation greenness as well as the length of the vegetation period are closely related to the seasonality of regional climate.

The seasonal growth of vegetation directly influences the seasonality of regional and global atmospheric CO₂ concentration (D’Arrigo et al. 1987; Keeling et al. 1996; Myneni et al. 1997a). Thus, it plays an important role in terrestrial carbon cycling studies (Verstraete et al. 2008; White and Running 1999, among others). Hence, monitoring the seasonality of vegetation is of particular importance to study terrestrial productivity (Delbart et al. 2005) and to understand vegetation dynamics (Kaduk and Heimann 1997; Bradley et al. 2007; Turner et al. 2007). Phenological signals represent a sensitive indicator, as they may shift because of climatic changes (Myneni et al. 1997a) or large-scale disturbances (Potter et al. 2003) on an annual basis. Therefore, the long-term monitoring of phenological processes plays a significant role in global climate change research (de Wit and Su 2005; Zhou et al. 2001; Kang et al. 2003; Menzel 2002; Penuelas and Filella 2001).

Climate and carbon models support the investigation of global dynamic processes (McCloy and Lucht 2001) and are of great importance to simulate past and future climate under changing global conditions. However, our experience with climate modeling shows that phenology is a critical aspect in global climate models. Phenology models are problematic because of the large uncertainties in modeling. So far, only a few studies assess phenology models with satellite observation data (e.g., Lüdeke et al. 1996; Randerson et al. 2009), and the reason for this clearly lies in the difficulty of determining comparable phenological events from different datasets, models, and remote sensing observations.

Ground-based phenological records are usually limited to the phenological status of single species (White et al. 2002) and are therefore selective by nature. However, satellite-based remote sensing data offer the opportunity to map the areawide seasonality as an aggregation of
greenness events (Kang et al. 2003) at different spatial (e.g., ecosystem-scaled signals; Reed et al. 1994; Schwartz et al. 2002) as well as temporal scales. Phenological signals appear in time series of various biophysical variables such as the leaf area index (LAI) or fraction of absorbed photosynthetically active radiation (fAPAR) that can be derived from satellites, and can be calculated from climate models.

While in situ phenological records are based on common standards for the definition of phenological events [see, e.g., the comprehensive overview of Nekovar et al. (2008)], no such standard definitions exist for remote sensing applications (Verstraete et al. 2008). Several methods have been developed to derive phenological events (e.g., the onset of greening, or the length of growing season) from annual vegetation curves. These methods are mostly based on vegetation index thresholds, temporal derivatives, moving averages, curve-fitting procedures, and so on [see, e.g., the overviews given by Reed et al. (1994), Zhang et al. (2003), and Linderholm (2006)] and are typically adapted to regional scales and specific types of biomes [e.g., arctic biomes (Markon et al. 1995), alpine vegetation (Studer et al. 2007), boreal and deciduous forests (Delbart et al. 2005, 2006), temperate mixed forests (Kang et al. 2003; Chen et al. 2005), or savannas (Heumann et al. 2007)]. Zhou et al. (2001, 2003) and Myneni et al. (1997a) have studied seasonal changes on the northern latitudes using Normalized Difference Vegetation Index (NDVI) data at a continental scale on the northern latitudes using Normalized Difference Vegetation Index (NDVI) data at a continental scale. These methods appear in time series of various biophysical variables such as the leaf area index (LAI) or fraction of absorbed photosynthetically active radiation (fAPAR) that can be derived from satellites, and can be calculated from climate models.

The major objectives of the present paper are to develop a robust method for the estimation of phenological information from satellite remote sensing data at the global scale and to compare different state-of-the-art long-term satellite-derived vegetation data records. While previous studies focused on the estimation of specific phenological events (e.g., spring date), the current paper introduces a new method that allows for the robust identification of global seasonal signals from multisensor time series with a special focus on the difference in the phasing of the annual characteristic signal.

The method is developed using three different long-term satellite vegetation datasets [Sea-Viewing Wide Field-of-View Sensor (SeaWiFS), Carbon Cycle and Change in Land Observational Products from an Ensemble of Satellites (CYCLOPS), and Moderate Resolution Imaging Spectroradiometer (MODIS)] and is applicable for more generic implementations, such as the intercomparison of satellite data products with results from global climate models. This would have the potential to constrain the simulations of global carbon and climate models (e.g., Knorr et al. 2010; Rayner et al. 2005) and help to improve their parameterizations (Stöckli et al. 2011). It is therefore optimized for the comparison of characteristic seasonal signals in multiannual datasets.

Furthermore, we introduce the term “greening phase” that is used throughout the article to emphasize the difference from studies that focus mainly on the extraction of single phenological events (e.g., “green-up” or greenwave). The study will apply the proposed greening phase analysis method on four global multiyear satellite datasets. It is our hypothesis that all datasets should show similar patterns if the method works well as long as the phenological signal is well captured in the different data products. The study will focus on the application of the method and illustrate its robustness across varying input datasets, and does not aim to evaluate the accuracy of any particular product. Comparison studies already exist for that purpose (e.g., Weiss et al. 2007; Verstraete et al. 2008; McCallum et al. 2010).

The used remote sensing datasets are described in section 2 and the method to derive global greening phase patterns is introduced in section 3. A global analysis of the derived greening phase patterns is presented in section 4 and the results are discussed in section 5. Conclusions can be found in section 6.

2. Data

Time series of four independent global fAPAR products are analyzed to detect intra-annual greening phase patterns. We use fAPAR because it is directly measured the same global mixture and patterns.
linked to vegetation growth and phenology (Gobron et al. 2006b). As fAPAR is typically calculated from visible and near-infrared (VIS/NIR) bands, it is well suited to provide information about the status of the vegetation on the ground (Gobron et al. 2006a). Data from the SeaWiFS, the VEGETATION sensors, and MODIS sensors are used. These were selected as they are based on state-of-the-art retrieval algorithms. In addition, we include fAPAR data derived from the Advanced Very High Resolution Radiometer (AVHRR) into our analyses that provide long-term records since 1981, which makes it a suitable candidate for comparison with, for example, dynamical vegetation models as used in coupled climate models. All data products will shortly be described in the following. Corresponding quality flags, and in the case of SeaWiFS, MODIS, and AVHRR data, an aggregation to a monthly temporal resolution, have already been applied by the data providers. For more technical information the reader is referred to the given references. An overview of the dataset properties can be found in Table 1.

The time series of the SeaWiFS fAPAR data (available since September 1997) are calculated from top-of-atmosphere (TOA) red and near-infrared reflectances. Blue band information is used to remove atmospheric effects. The generic algorithm is optimized to minimize atmospheric and geometric effects in the fAPAR data product (Gobron et al. 2002, 2006b). This is done by a two-step procedure: first, the spectral bidirectional reflectance factors (BRFs) that were measured in the red and near-infrared bands are rectified so that atmospheric and angular effects are eliminated as best as possible. In a second step, BRFs and reflectances are recombined to calculate fAPAR values with a radiative transfer model (RTM) approach (Gobron et al. 2008). The data products are available as monthly averages from the European Joint Research Center (http://fapar.jrc.ec.europa.eu/) at a spatial resolution of 0.5°. The temporal aggregation is described in Gobron et al. (2006a), following Pinty et al. (2002) with a gap-filling algorithm that chooses the value that is the closest to the temporal average value derived from the compositing period. An analysis of the information content of the dataset at the global scale has been published by Gobron et al. (2010). For this study, 8 years have been evaluated (1998–2005).

The second fAPAR product used in this study comes from the CYCLOPES project. The CYCLOPES products are generated under the Fifth European Community Framework Programme (EU/FP5) CYCLOPES project, using algorithms developed by the Centre National d’Études Spatiales (CNES), Centre National de Recherches Météorologiques (CNRM), Institut National de la Recherche Agronomique (INRA), and Novelbis. They are produced and provided by the Pole d’Observation des Surfaces Continentales par Teledetection (POSTEL) Service Centre at Médias-France (http://postel.mediasfrance.org). After cloud screening (using the GLC2000 land cover map), atmospheric correction, bidirectional reflectance distribution function (BRDF) normalization, and temporal composition, fAPAR values are calculated from top-of-canopy (TOC) reflectances of the blue, red, NIR, and shortwave infrared (SWIR) bands with an algorithm based on a neural network approach trained with a radiative transfer model (Baret et al. 2007). The CYCLOPES fAPAR product is available with a spatial resolution of 1 km² as well as a temporal resolution of 10 days. For our purposes, we resampled the dataset to monthly values with a spatial resolution of 0.5°. Nine years of the CYCLOPES dataset have been evaluated (1999–2007).

<table>
<thead>
<tr>
<th>Sensor</th>
<th>SeaWiFS</th>
<th>VGT</th>
<th>MODIS</th>
<th>AVHRR</th>
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<tr>
<td>Platform</td>
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<td>SPOT</td>
<td>Terra, Aqua</td>
<td>National Oceanic and Atmospheric Administration (NOAA)</td>
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<td>TOC reflectance B, R, NIR, SWIR</td>
<td>TOC reflectance, NDVI max 7</td>
<td>NDVI values R, SWIR</td>
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<td>MOD12,8 biomes</td>
<td>6 LCTs</td>
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<td>Neural network trained with RTMs</td>
<td>RTM vs LCT (NDVI backup)</td>
<td>Formulas based on 3D RTMs</td>
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<td>Yes</td>
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<td>JRC Italy CYCLOPES</td>
<td>Boston University</td>
<td>Boston University</td>
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</tbody>
</table>
The third fAPAR dataset is derived from the National Aeronautics and Space Administration (NASA) MODIS sensor (level-4 MCD15A2, available since March 2000) as a combined product from Terra [Earth Observing System (EOS) AM] and Aqua (EOS PM) of collection 5. It is provided by Boston University (http://cliveg.bu.edu/modismisr/) with a monthly temporal resolution and a grid spacing of 4 × 4 km². The fAPAR values were calculated from the atmospherically corrected red and near-infrared reflectances using up to seven short-wave spectral bands for the algorithm of Knyazikhin et al. (1998, 1999). The fAPAR calculation is based on a land cover map MOD12, and a three-dimensional RTM inversion in the first place. If the RTM approach fails, a backup algorithm based on vegetation indices is used. For our purposes, we resampled the MCD fAPAR product to a spatial resolution of 0.5° by arithmetic averaging. Seven years of data (2003–09) have been evaluated for this study.

Hence, the study is based on three multiyear time series from 1998 to 2009. The time series of the described datasets from the three sensors only overlap for 3 years (2003–05). Nevertheless, for statistical reasons, at least 7 years are evaluated from each sensor. It is assumed that this will not affect the analysis, as this is focused on the extraction of the characteristic seasonal signal from the observational data. The data products are in a coarse spatial and temporal resolution, where only very drastic changes in the phenological signals between 1998 and 2009 are detectable from the data.

In addition to the other three datasets, we evaluate a global AVHRR fAPAR product for comparison reasons. The global AVHRR fAPAR data product used (available since August 1981) is based on the monthly data product provided by Boston University (http://cliveg.bu.edu/modismisr/), which estimates biome-specific fAPAR from Pathfinder AVHRR Land (PAL) NDVI values using radiative transfer (RT) simulations and field surveys (Myneni et al. 1997b). It is provided in a spatial resolution of 0.5°. Eight years (1993–2000) of the AVHRR time series are used for the present study. The AVHRR PAL data are cloud screened, composited, and corrected for Raleigh and ozone effects, but not corrected for aerosol scattering and water vapor absorption (Myneni et al. 1997b). The incomplete atmospheric correction might result in remaining atmospheric artifacts in the AVHRR data product, and it is therefore only handled as an additional dataset in this evaluation study.

3. Methods

The seasonal signal is extracted from the annual time series of satellite measurements on an individual gridpoint basis. The season is identified by the algorithm, and the relative contribution of each measurement to the total greening phase is estimated. The algorithm can be applied to any kind of satellite data products with relevant sensitivity to vegetation phenology.

a. Screening for seasonality

The greening phase pattern analysis should only be applied to grid cells with seasonality (i.e., time series that contain one or two oscillations per year). First, from each of the multiyear time series of the datasets, we subtract the mean value of each long-term time series to clarify possible seasonal information. Then, we identify regions with low or no seasonality as well as potential erroneous remote sensing data by means of a fast Fourier transform (FFT) analysis of the multiyear time series (i.e., grid cells with seasonal information are designated if they feature a maximum peak at one or two oscillations per year). A mask of regions without significant seasonality has been derived from each of the datasets. All masks have been combined to a single mask that is used in the further analysis such that grid cells are ignored if they are rejected in at least one of the four datasets.

b. Greening phase analysis

For each grid cell and each year the data are collected into a measurement vector \( \mathbf{x} = (x_1, x_2, \ldots, x_N) \), where \( N \) is the number of measurements per year, and \( x_i \) are regularly spaced measurements at times \( i = 1, \ldots, N \).

Sample plots of times series of fAPAR products for different biomes are shown later (see Fig. 6). It is clearly seen that the individual products show considerable biases while they maintain significant information about the vegetation seasonal cycle. These differences might result from, for example, different product definitions or algorithms and prohibit a direct comparison between the datasets. To allow for the comparison of the phenological signal in the time series, the bias in the time series is removed by subtracting the annual minimum value \( j_0 \) of each annual time series from all elements (i.e., \( \mathbf{x} = \mathbf{x} - j_0 \)).

The greening phase analysis is then derived in three steps: First the data vector is normalized to extract the greening phase, a cyclical permutation is then applied to center the time series around the maximum phenological stage, and finally the greening phase calculation is applied.

Let us consider the area under the curve defined by \( \mathbf{x} \) to represent the total greening phase of a given year. By normalizing the vector [Eq. (1)], each element \( y_i \) represents the relative contribution from time interval \( i \) to the total greening phase of a grid cell in the particular year (see Fig. 1).
These relative values provide a robust estimate of the phenological signal and allow for an intercomparison between different grid cells as well as different datasets, even if the data represent slightly different physical quantities. For example, in the present study we compare satellite-derived vegetation index data although different atmospheric corrections were used in their derivation. Another example would be the comparison of satellite data products with model simulation results. Such comparisons across vegetation data of different type are possible because the greening phase should be largely independent from how it is observed:

$$y := \frac{x}{||x||} \quad \text{where} \quad ||x|| := \sum_{j=1}^{N} |x_j|. \quad (1)$$

In a second step, the annual fAPAR curves are normalized in time. The starting point of each curve is chosen to be at the minimal vegetation response of a given year (i.e., each vector is cyclically shifted so that it begins with zero).

If $i_0$ is the time step at which $y_{i_0} = 0$, then

$$z_k = y_{(i_0 - 1 + k) \mod N}, \quad k = 1, 2, \ldots, N \quad (2)$$

are the components of the cyclically shifted vector such that $z_1 = 0$. In case that $i_0 > 1$, the vector would consist of parts from two contiguous vegetation periods. Therefore, the annual cycle of grid cells of the Northern Hemisphere is calculated from January to December, and of grid cells of the Southern Hemisphere from July to June of the following year.

Third, we determine the point in time when a given fraction $q$ (e.g., 30%) of the total greening phase is reached. This point in time corresponds to the lowest index $t'$ of $z$ for which $\sum_{i=t'}^t z_i \geq q$. Finally the index $t'$ of $z$ is transformed back to the index $t$ of $y$ by $t = t' + i_0 - 1 \mod N$. Hence, the greening result for fraction $q$ of the annual time series $x$ is $g(x, q) = t$.

As the data normalization is based on the entire time series, the shape of the time series might in theory affect the greening phase calculation. Hence, greening phase patterns between unequally distributed time series may lead to phase shifts, although start and end of season is synchronous. However, sensitivity studies showed (see appendix C) that for curves observed from natural vegetation the influence of different shapes is smaller than 1 month, and thus smaller than the temporal resolution of the used datasets.

c. Greening phase pattern comparison

To analyze the greening phase shifts in the derived patterns one might subtract the individual time series on an annual basis. However, to derive the characteristic phenological pattern from different datasets the use of multiannual time series is necessary. This is of particular importance if remote sensing data products will be compared against climate model simulation results, as climate models are expected to reproduce the characteristic phenological cycle, but not necessarily individual annual anomalies. Thus observations from a particular year cannot be directly compared against model simulations of the same year.

By analyzing the greening phase for each year of the observation periods, a frequency distribution is obtained characterizing the temporal greening evolution for each grid cell for the whole period (Fig. 2). A two-sampled Kolmogorov–Smirnov test for similarity is used to evaluate the similarities between the frequency distributions of the different datasets. It is well suited for datasets with small and different sample sizes (Massey 1951).

The mode values of the frequency distributions represent typical points in time, when a certain phasing of greening is reached for a grid cell during the observation period. A comparison of greening phase patterns

**FIG. 1.** Phasing calculation of a sample normalized annual vegetation product curve.

**FIG. 2.** Two example patterns derived from multiyear time series, showing frequency distributions of the points in time, when a given fraction of greening phase for one grid cell is reached. Differences between the greening phases are defined by calculating the temporal shift between the mode values of the frequency distributions.
between two different datasets is obtained by calculating the temporal shift between the mode values for each of the greening fractions (see Fig. 2). Differences between the greening phase patterns are thus displayed as differences in the phase of the seasonal signal.

To simplify the comparison and the discussion of the phasing aspect of the four datasets on a global scale, results have been condensed into time–latitude diagrams. These summarize the results per latitude with stepwise fractions from 5%–95% of the total greening phase per year (see, e.g., Fig. 3). Each fraction is represented by the mode values of each latitude. For each latitude, all grid cells over the full time periods have been evaluated and composed into greening phase maps, where each grid cell is represented by the mode value over the full time period for a certain fraction of the greening phase. Only patterns are displayed if at least 10 grid cells per latitude contain valuable information.

The distribution of the continents, as well as the missing desert and alpine regions, cause a division of the diagrams into horizontal zones. These zones reflect the phasing of the predominant vegetation (major global biomes; e.g., Whittaker 1975) that cover the different continents.

4. Results

a. Global greening phase patterns

The phasing of the greening cycle has been calculated from the four independent fAPAR products: SeaWiFS, CYCLOPES, MODIS, and AVHRR. Figure 3 shows a time–latitude diagram from each dataset that contains the phasing of the greening cycle for 1 year, beginning with the start of greening at fraction 5% and the end of season at fraction 95%. Examples of greening phase maps are also given for fractions of 30%.

In general, the greening phase results from the four different sensors show similar global patterns. The beginning and end of the seasonal cycle are nearly always analogous for all four datasets, but the timing of the succession of the greening phase varies.
The range from 80° to 30°N displays mainly signals from the vegetation cover of the North American and Eurasian continent. The northern high latitudes are dominated by the biomes tundra and taiga with a short vegetation period. Temperate zones (50°–30°N) with temperate forests, temperate shrubs, and grasslands follow. In these regions, SeaWiFS shows a faster progress of greening phase patterns, and CYCLOPES shows a slower progress in comparison with the other datasets. This can be seen from the diagrams (see, e.g., the greening phase fraction of 50%). CYCLOPES reaches this step of the greening phase succession in August, whereas SeaWiFS, MODIS, and AVHRR show this point in July. For 60% of greening phase, SeaWiFS is the only dataset that indicates July; the other datasets reach this point in August. At the end of the vegetation period (from fractions 80% to the end), AVHRR shows a gradual succession of the greening phase according to latitude. The other three datasets show a more or less crisp transition.

From 30° to 15°N, the greening phase of the tropical seasonal forests and grasslands of the Indian subcontinent are reflected. All sensors show similar beginnings of the greening phase, but different lengths of the vegetation period. CYCLOPES and MODIS close the greening phase of this region in February, whereas AVHRR shows March. SeaWiFS shows January and displays a faster progress of the greening phase succession.

From 15°N to 0°, the plant cover of the central part of the African continent dominates the greening patterns. All four sensors show equivalent results.

The zone from 0° to 30°S displays the signals from South America and Africa with tropical grasslands and shrublands, savanna, and tropical rain forests. Here again, SeaWiFS displays a faster progress of the greening phase succession. At greening phase fraction of 40%, it shows January and February, whereas the other sensors display February and March. In comparison to the other sensors, AVHRR shows a longer vegetation period that starts in October instead of November and finishes in August instead of July.

Between 30° and 40°S, phasing patterns from the temperate vegetation of the southern part of Australia are depicted. All four sensors show more or less similar results for this zone.

The southernmost zone (40°–55°S) reflects phasing signals from the temperate and mountain forests of Chile but will not be interpreted here because most patterns of this region are derived from less than 10 grid cells per latitude. In the following shift calculations, these latitudes are excluded from the analyses.

b. Greening phase pattern comparison of SeaWiFS, CYCLOPES, and MODIS fAPAR products

The three fAPAR products from SeaWiFS, CYCLOPES, and MODIS have been evaluated by the greening phase analysis. The results discussed in this section are briefly summarized in Table 2. Figure 4 shows how similarly the three fAPAR products from SeaWiFS, CYCLOPES, and MODIS performed. The temporal shift between the greening phase results of these datasets is combined into time–latitude diagrams. They show the mean time shifts between different greening fractions per latitude, as well as shift maps for greening phase fractions of 15%, 50%, and 75%. This gives an impression of how the different datasets perform during the succession of the greening phase and reveal the regions where the datasets differ from each other.

The Kolmogorov–Smirnov test for similarity shows significant similarities between the three fAPAR products at 95% confidence level on the global scale (shown in appendix B). Generally, the shift results from the sensors indicate that the timing of the seasonal phases varies between −1 and +1 month in most cases and shows a shift of 0 months for large parts of the greening phases. Similarities and differences will be presented in the following subsections, and will be discussed and underlined with time series from the datasets in section 5.

c. High northern latitudes 75°–65°N

The latitudes between 75°N and approximately 65°N are dominated by arctic tundra vegetation with a winter
pause due to polar night, winter dormancy, and snowfall. Our evaluations show that, in general, the annual greening phase patterns of the three sensors agree for the observation periods. For the high latitudes of Siberia, CYCLOPES and SeaWiFS show earlier endings of the vegetation period than MODIS, which confirms the impression from Fig. 3 that CYCLOPES shows the shortest vegetation period in this area, and MODIS the longest.

d. Evergreen and deciduous needleleaf forests of the latitudes 65°–50°N

Along the boreal belt of North America and Eurasia, the results from Fig. 3 clearly show that the three sensors agree very well for the second half of the vegetation period, but they differ mostly between 1 and 3 months in the beginning. The largest differences occur between SeaWiFS and CYCLOPES. SeaWiFS shows earlier and CYCLOPES later onsets in comparison with the others. Along the eastern Russian coast, SeaWiFS reaches the 50% fraction of the greening phase 1 month ahead.

Outstanding very large shifts are visible in the maps that are derived from SeaWiFS sensor data on the right side of Fig. 4. They show considerable differences between the greening phase patterns in a small area along the western coast of Canada (British Columbia). The estimated shift between the sensors is 3–6 months.

e. Temperate biomes of the northern latitudes (50°–30°N)

The latitudes between 50° and 30°N are dominated by temperate forests as well as temperate grasslands, deserts, and Mediterranean shrublands. Generally, these latitudes show similar patterns in the greening phasing from the three sensors. The greening phase patterns from CYCLOPES and MODIS fAPAR correspond especially well. The comparison with SeaWiFS agrees for the most parts of the greening phase. Earlier endings of the SeaWiFS vegetation period on the European continent are visible, primarily in the comparison of SeaWiFS with CYCLOPES data. The time–latitude diagrams show small shifts between the sensors that occur
sporadically only for single fractions in the second half of the vegetation period between CYCLOPES and SeaWiFS as well as MODIS and SeaWiFS.

f. (Sub)tropical seasonal forests of India and southeastern Asia (30°–15°N)

The latitudes between 30°N and approximately 15°N are dominated by tropical seasonal forests and grasslands, mainly occurring on the Asian continent, partly a monsoon region with two annual seasons. Comparison patterns of greening phase calculations show equal onsets of greening, but a systematic delay of MODIS curves of 1–3 months in Southeast Asia for the rest of the vegetation period. On the Indian peninsula, SeaWiFS departs from the other two sensors, being ahead for 1 month at the 50% fraction of the greening phase.

g. African savanna and South American tropical grassland (15°–5°N and 5°–30°S)

The latitudes between 15°N and approximately 5°N and between 5° and 30°S are dominated by savanna and tropical grasslands, occurring on the African and South American continent as well as on the northern coast of Australia. Very good agreement can be found among the sensors for large areas of these biomes. In the Southern Hemisphere, SeaWiFS tends to be 1 month ahead of the other sensors for the second half of the vegetation period.

h. Tropical rain forests (5°N–5°S)

Tropical rain forests define the latitudes adjacent to the equator between 5°N and 5°S. Most of the grid cells belonging to this biome have been masked out because no maximum peak at one or two oscillations per year was found by the FFT analysis. Still, some of the evergreen regions typically show a small annual amplitude and have therefore been evaluated. Large shifts up to 6 months are detected by the greening phase analysis between the sensors. It seems that MODIS and SeaWiFS show similar patterns on the South American continent, whereas CYCLOPES and SeaWiFS correspond better in Africa.

i. Australian and South American shrubland (30°–40°S)

The between 30° and 40°S are dominated by shrublands on the Australian and South American continents. Other biomes of this latitude are mainly deserted and therefore excluded from the analysis. In comparison with the other sensors, CYCLOPES shows an earlier onset of spring in South America. SeaWiFS indicates a later ending of the vegetation period in Australia.

j. Combined analysis results

The results from the greening phase analysis derived from three independent fAPAR products reveal large areas of similarities as well as regions where the sensors show shifts between the seasonalities. In this subsection, a practical overview of the greening phase patterns will be given. The pattern comparison results from the three sensors SeaWiFS, CYCLOPES, and MODIS are aggregated to a red–green–blue composition map (Fig. 5). Colors represent the average of the absolute shift among greening phase patterns of two sensors in months. High color saturation means high agreement between the sensors; low saturation (i.e., shift of maximum 6 months) means no agreement.

The shifts between MODIS and SeaWiFS are colored in red, the shifts between CYCLOPES and SeaWiFS are colored in green, and the shifts between MODIS and CYCLOPES are colored in blue. By additive color mixing white regions indicate regions with a high agreement between the seasonality of the three datasets, and colored patches indicate regions where two sensors agree and one does not.

The map shows that globally for most regions all three sensors have similar seasonalities. Red patches on the map mean no shift between MODIS and SeaWiFS but high disagreement of CYCLOPES. Green regions indicate corresponding SeaWiFS and CYCLOPES data and disagreeing MODIS data, whereas blue patches show the regions, where SeaWiFS does not correspond to the other two sensors. Most patterns that have been mentioned before are displayed in the pattern comparison map. Prominent regions where the sensors disagree for more than 3 months are the tropical evergreen forests of South America and Africa, the western coast of North America, and the southern part of Southeast Asia, and smaller spots occur on the Eurasian continent. The boreal regions of North America and Eurasia show a very continuous belt with a shift of 1–3 months between the three sensors with variegating agreements. Especially along the coasts of the continents, slight shifts are visible. In the following discussion section, further insights into the datasets will be given.

5. Discussion

In this section, the results from section 4 will be further analyzed. It has been shown that the different datasets show consistent results a large portion of the globe. The analysis will therefore focus in the following mainly on the differences between the different datasets. These differences will be discussed and compared to other studies that evaluate seasonalities between vegetation
products. Selected time series for different biomes are shown in Fig. 6, including the time series of AVHRR.

a. High northern latitudes

The greening phase patterns from arctic regions mostly reveal similarities but show small differences among the sensors for the eastern parts of Siberia. Figure 6a shows a sample of the underlying time series of this area. The MODIS time series has an extended autumn curve that is not in agreement with the other two (three including AVHRR) sensors.

Earlier comparison studies in high northern latitudes (e.g., Tian et al. 2004; Yang et al. 2006; Weiss et al. 2007) referred MODIS divergences to its backup algorithm if its main algorithm failed over snow-covered grid cells. However, the collection 5 dataset, which was used in the present study, is considered to be much more improved, including in arctic regions (Friedl et al. 2010). However, for most parts of the tundra regions, and for nearly all fractions of the greening phase, the three sensors show similar seasonalities and can be compared with each other by the greening phase analysis.

b. Boreal zone

The boreal biome of North America and Eurasia comprises mainly evergreen needleleaf forests, and the eastern parts of Siberia are covered with large areas of deciduous needleleaf forests. For the evergreen needleleaf areas (visual comparison with GLC2000 land cover map), the greening phase results show shifted patterns for the three sensors. Two sample time series from the Siberian taiga can be found in Fig. 6: B1 from evergreen needleleaf forest, and B2 from deciduous needleleaf forest. The example from deciduous needleleaf forest shows well-defined and similar seasonalities among the sensors. The example from the evergreen needleleaf forest, instead, shows that the annual minima of the sensors’ time series do not correspond with each other. This prevents the greening phase algorithm from starting at the same step in time. Therefore, the greening phase analysis measures shifts of 1–3 months in the beginning of the vegetation period between the sensors.

Many evaluations from remote sensing derived fAPAR exclude these regions from analyses (e.g., Gobron et al. 2006a). The reason for this clearly lies in the difficulty of coping with winter values due to snow and cloud occurrences, and a low solar zenith angle (Wang et al. 2004; Beck et al. 2006; Garrigues et al. 2008). This complicates the determination of winter fAPAR values. SeaWiFS and MODIS have their annual minimum in December, whereas CYCLOPES shows it in March. This is consistent with Fig. 3, which revealed that CYCLOPES shows the slowest progress of greening phase succession from all four sensors. McCallum et al. (2010) cite large variation in the winter months of MODIS, CYCLOPES, Joint Research Center (JRC) SeaWiFS, and GLOBCARBON.
fAPAR, and they detect poorest agreement among the datasets over needleleaf forests. Their finding that in evergreen needleleaf forests MODIS tends to start earliest in spring can also be taken from our time series, but this result is superposed by the high fAPAR value of the SeaWiFS and CYCLOPES winter period.

The large discrepancies found in British Columbia are shown in the time series of Fig. 6, B3. While the AVHRR, CYCLOPES, and the MODIS sensors show a vegetation period with a peak in August, as would be expected for the climate of western Canada, the SeaWiFS product has its maximum in January. This is obviously associated with problems with this specific SeaWiFS data product in this case.

It can be concluded from our evaluations of boreal ecosystems that the different sensors show similar seasonality. The greening phase analysis detects existing disparities among the time series of the datasets. The interpretation and equalization of the greening phase results with seasonality is hindered by the difficulty of finding the true beginning of the vegetation period after noisy winters in the fAPAR products, and it strongly be linked with the evergreenness in these regions. Deciduous land cover types of these latitudes perform very well in the evaluations. To minimize the potential influence of snow on the data analysis, further studies could be based on the NDWI (Delbart et al. 2005), which could result in a more robust estimate of the greening phase in these problematic areas.

c. Temperate regions

Most parts of the temperate biomes of the Northern Hemisphere show very consistent results across the different sensors. Only some of the outliers will be discussed in the following.

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**Fig. 6.** Original and normalized fAPAR time series from samples of chosen regions.
Time series 6, C1, shows that the seasonality of CYCLOPES does not correspond to the other sensors at a small stripe along the western coast of the United States. The greening phase analysis reveals very different annual minima from the three sensors but better agreements between SeaWiFS and MODIS data.

The European western coast displays shifts of more than 1 month between the sensors. The British Islands, parts of France, and the northern coast of Spain show disagreements of MODIS (northern areas) and CYCLOPES (France, Spain). Time series 6, C2 (from Spain) reveals a general low seasonality from the original datasets.

Larger parts of Europe show shifts of 1 month between the sensors. Time series 6, C3 from Germany reveals slightly shifted starts of the vegetation period among the sensors. In this sample time series, CYCLOPES and MODIS start its season 1 month ahead of SeaWiFS, whose curve shows a much more distinctive seasonality in comparison with the other sensors. The step in time of the annual maximum agrees among the sensors. Larger disagreements can be seen at the end of the vegetation period. CYCLOPES elongates its vegetation period for 1–2 months, which is consistent with Fig. 4, where CYCLOPES time series tend to have a later end of the vegetation period for parts of Europe.

For temperate regions it can be concluded that most areas show similar seasonalities from the three sensors. Small regions occur, mainly in areas with a low seasonality in general, where the greening phase analysis depicts deviations of the underlying time series. On the one hand, true differences among the sensors are found. On the other hand, shifts can result from different annual minima or the curves, leading to different successions of the greening phases.

d. India and Southeast Asia

The latitudes between 30°N and approximately 15°N perform very well in the greening phase analysis. In Fig. 5, Bangladesh and Southeast Asia stand out from the other areas with high agreement. To underline the results, three sample time series are given in Fig. 6: D1–D3. Sample D1 shows the fAPAR curves from the northern part of India with a biannual seasonality. High agreement among the different curves can be found apart from AVHRR, which extends its second vegetation period for 1 month.

D2 represents the time series from Bangladesh that shows large shifts between the sensors on the comparison map. Also with a low seasonal amplitude in general, the curves display different seasonals, with annual cycles starting in August (CYCLOPES, MODIS) and in January (SeaWiFS). In comparison, plot D3 is derived from Southeast Asia, where MODIS deviates from the other sensors for approximately 4 months. This explains the results from the greening phase, namely that MODIS shows a systematic delay for all fractions in this region. Although the MODIS combined data from collection 5 are considered to be of best quality, this region belongs to the few areas with a higher failure of the main algorithm (see Shabanov et al. 2007). Therefore, given the high precipitations combined with low seasonality, the MODIS backup algorithm might be the reason for the depicted differences.

We conclude that the greening phase analysis is able to compare regions with a biannual cycle, as long as the annual minima from various sensors harmonize—which is mostly the case in the regions with a certain degree of seasonality. Differences that have been detected by the greening phase analysis can clearly be assigned to true dissimilarities of the underlying time series.

e. African savanna, Australian shrublands

The different sensors show very similar results from the latitudes between 15° and 5°N as well as 5°–30°S. In case of the Northern Hemisphere, no shift in seasonality is visible from the greening phase results. Accordingly, the time series F1 in Fig. 6 gives an example of the sensor curves from the Sahelian zone with highly matching sensors.

In the Southern Hemisphere between 5° and 30°S, the greening phase analysis reveals that SeaWiFS seems to be 1 month ahead of the other sensors for the second half of the vegetation period. The time series F2 in Fig. 6 show an example grid cell from Zambia, and F3 plots the fAPAR curves of a grid cell from the northern coast of Australia. Both plots show well matching seasonalities but slight to clear divergences of the SeaWiFS product with regard to an earlier maximum and end of the season. As far as we know, no studies have yet compared the seasonality of different fAPAR products from these southern latitudes. But since the phasing of the seasonality is shifted, but similarly shaped, the divergence from SeaWiFS is most probably due to the temporal aggregations of the different fAPAR products. Reanalyses with higher temporally resolved datasets would then help to better understand our findings.

It follows from the evaluations of these latitudes that the greening phase analysis evaluates very well the matching seasonality for large areas. It detects a systematic and areawide shift from the SeaWiFS sensor for the second half of the vegetation period.

f. Tropical rain forests

Among the patterns of the Fig. 5, the tropical rain forests are by far the most eye-catching regions. Large shifts between the sensors are visible, and they cover
most parts of the tropics. Two sample time series can be found in Fig. 6, E1 (Brazil) and E2 (Congo). No clear onset of the vegetation period can be identified from the time series, which leads to a disagreement between the sensors. Again we can conclude that in tropical evergreen regions with the involved low seasonality, the greening phase analysis shows strongly shifted results if the annual minima from the datasets diverge. The clearly defined shape of these regions can be used to classify these regions after the analyses.

g. Data performance

The three fAPAR products from SeaWiFS, CYCLOPES, and MODIS are considered to be comparable with respect to atmospheric correction and product definition (McCallum et al. 2010). The results of the greening phase analysis reveal that we can accept the hypothesis that the three fAPAR time series derived from independent fAPAR products show similar patterns on the global scale at the 95% confidence level. Based on the monthly resolved datasets that have been evaluated in this study, only few remarkable shifts are visible. Most shifts stay in the range of ±1 month, which is the expected minimum shift for monthly resolved data. The shifts that are detected from our greening phase analysis rely on true dissimilarities of the time series. Larger identified differences between the three datasets are caused by either problems in one of the datasets (most likely influenced by clouds, rain, or snow) and/or by a general low seasonality of the input datasets.

A sensitivity analysis using MODIS data at 4 × 4 km² pixel resolution as well as on a 0.5° grid shows that the spatial upscaling is not influencing the greening phase signal as detected by the proposed method. Results of this analysis are provided in appendix C. This emphasizes the robustness of the proposed method across different spatial scales. Thus, detected differences in the vegetation phenology can be attributed to differences in the used data products.

Mahecha et al. (2010) analyze the temporal sampling in northern high latitudes for SeaWiFS fAPAR. They show that large areas are affected by gap filling due to the increased number of data gaps in this region. Since the greening phase method mainly provides information about the difference between characteristic seasonal signals, it is rather insensitive to local artifacts due to gap filling algorithms used by the data providers, which are typically based on mean seasonal climatologies.

It is an interesting fact that AVHRR data are available over 30 years, and its potential had to be tested concerning planned comparisons with long-term climate model outputs. As expected, AVHRR shows a large bias when absolute values from the four sensors are compared (see Fig. 6). Because of an incomplete atmospheric correction, fAPAR values are too high in most of the evaluated biomes, except for very dry regions such as the African savanna (see Fig. 6, F1). But the evaluations (Fig. 7) derived from AVHRR sensors show that although the vegetation seasonal cycle can be contaminated by atmospheric seasonal cycles, the greening phase method shows similar seasonal results on a global scale. The greening phase method extracts seasonal information and makes therefore AVHRR comparable. On the basis of our evaluations we can conclude that the AVHRR PAL fAPAR dataset performs in comparable ways. This is an interesting result concerning the probable usage of 30 years of AVHRR fAPAR data for comparison studies with time series derived from climate models.

h. Advantages and limitations of the method

The greening phase method is based on normalized time series to extract the greening phase signal and to compensate for systematic differences between different vegetation data. The method is able to detect differences, and maps the very regions on a global scale. In a further step, it is simple to examine the underlying time series whether disagreement is due to real shifts among the curves, noise, or problems of one dataset, or is an artifact of the algorithm. The proposed method provides insight into deviations during the full vegetation cycle. We can globally compare on a fraction-wise base (e.g., we can compare early fractions that would display spring features, as well as later fractions for autumn patterns). Fractions are needed to be able to compare the whole seasonal cycle. This provides more detail as to the actual differences between the different datasets and their timing. Often, datasets agree for most parts of the vegetation period, but differ in autumn. This can easily be shown by the greening phase analysis and is not possible using other methods.

The normalization is theoretically dependent on the shape of the investigated time series as the index calculation is based on data from the entire vegetation period. However, a sensitivity study (see appendix C) revealed that the method is a very robust estimator for the detection of the greening phase patterns if the time series have in general a sinusoidal shape with one or two peaks per year, as is typically the case for deciduous vegetation.

However, evergreenness and low seasonality in general limit the greening phase algorithm. Regions where noise deteriorates the minimum of the curve show small to large shifts in the greening phase pattern comparison. It is proposed to use the clearly defined shape of the so-defined regions as a classifier.

The developed method is very robust due to the normalization of the data prior to the data analysis.
Therefore, it can be applied on a global scale, to uniseasonal as well as biseasonal regions, and to various temporally as well as spatially resolved data. The performed analysis identifies the regions where remote sensing datasets can be used as a reliable reference, as well as the regions where the used remote sensing datasets differ from each other. Certainly, correlation between the datasets does not automatically imply accuracy (McCallum et al. 2010), but it does give some guidance.

The comparison map shows the regions where the datasets agree with a certain probability. For large areas of the globe (e.g., temperate zones), this probability would be very high (i.e., in these areas, existing datasets are able to detect similar results). In tropical rain forests, the uncertainty would be very high. We expect promising results concerning comparison studies with outputs from climate models. If the greening phase results from these outputs stay within the probability range of the existing datasets, the modeled parameters seem to be of satisfactory quality.

6. Conclusions

The proposed method has been proven to provide a robust approach to identify and quantify global greening phase patterns. Three state-of-the-art global fAPAR datasets have been analyzed and show very consistent results at the global scale. We therefore conclude that each of the datasets contains reliable information on the vegetation phenology for large parts of the globe. However, distinct differences have been also observed for single datasets at the regional scale. Some of these reported differences could be attributed to well-known caveats of single datasets in particular regions, which were already published in the literature. However, deviations of a single dataset from others do not necessarily imply that the deviating dataset is wrong. We therefore recommend always analyzing results from various global vegetation products when using the proposed methods for global phenology analyses.

Results from a long-term AVHRR data record have been analyzed and compared against the results from
the three state-of-the-art satellite vegetation data products. Preliminary results showed that the AVHRR fAPAR product provides very consistent seasonal information compared to the other data products. This is of particular interest for applying the method on longer time scales for intercomparison against, for example, dynamic global vegetation models (DGVMs) as the AVHRR record comprises more than 30 years of data. An application of the method for the benchmarking of DGVMs is planned for further studies.

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APPENDIX A

Greening Phase Pattern Comparison Using the AVHRR fAPAR Product

The greening phase results from the AVHRR data product show relatively high agreement in comparison with Fig. 4. Shifts mostly stay in the range of ±1 month. The underlying time series of chosen grid cells have been shown in Fig. 6. Although the datasets are derived from different time periods, it seems that similarities are not related to that: the highest correlations, especially in the Northern Hemisphere, can be found with the MODIS data, which is the most recent datasets of all four. The lowest agreement is shown in the beginning of the vegetation period for northern high latitudes versus

Fig. B1. Results from the Kolmogorov–Smirnov test statistics: (left) p values of comparisons with two sensors and (right) rejected grid cells below the significance level of 0.05.
CYCLOPES, and in Asian regions versus SeaWiFS for the second half of the vegetation period. This confirms previous results. The very high agreement among AVHRR and MODIS data implicates the possibility that the analog preprocessing done by Boston University is responsible. This would mean that data preprocessing, geocorrection, and scaling procedures would more significantly influence the datasets than a different fAPAR algorithm and applied (or not applied) atmospheric corrections. Since the seasonalities from AVHRR and MODIS correspond with the other fAPAR products in large parts of the world, we propose two findings from our results: First, the AVHRR data depict seasonality in a comparable way. Second, by applying the greening phase method, lacking atmospheric corrections do not disturb. This is a challenging result with respect to further studies, where we will exploit the full time series from 1982 to the present.

APPENDIX B

Results from the Kolmogorov–Smirnov Statistics

The results from the Kolmogorov–Smirnov test are displayed in Fig. B1. The maps on the left show the p value, ranging from 0 to 1, of the test statistics. It is visible that most parts of the globe show p values in the range from 0.4 to 1. Regions that show shifts in the greening phase analysis (e.g., boreal regions) show not as good results in the range below 0.4. Since the data comparison receives very high similarities for all fractions, only a few grid cells with a p value below 0.05 have to be excluded, which can be seen in the maps on the right.

APPENDIX C

Sensitivity Studies

a. Influence of spatial resolution on the greening phase results

We tested the spatial variability of the used MODIS combined dataset (see Fig. C1). Greening phase patterns were calculated from 4 × 4 km² resolved fAPAR values as well as from upscaled fAPAR values to 0.5°. Results were then compared against each other. The upscaled greening phase patterns agree with the greening phase patterns derived from the highly resolved imagery. Therefore, we advance the view that our proposed method does not bring artifacts into the shown results.

b. The influence of curve shapes on the greening phase results

We performed an additional sensitivity study (Fig. C2) that quantifies the effect of different curve shapes on the method. Different shapes of typical seasonal vegetation curves were assumed and compared against a nearly sinusoidal vegetation curve. It shows that the curve shape does not influence the analyses to a certain degree, until curves are too different. Then, results are influenced by the shape, but shifts stay in the
range of ±1 month. Very different curves depict a different seasonal signal and therefore show higher shifts in the greening phase analysis.

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