Chapter 7
TIMESAT: A Software Package for Time-Series Processing and Assessment of Vegetation Dynamics

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Abstract Large volumes of data from satellite sensors with high time-resolution exist today, e.g. Advanced Very High Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS), calling for efficient data processing methods. TIMESAT is a free software package for processing satellite time-series data in order to investigate problems related to global change and monitoring of vegetation resources. The assumptions behind TIMESAT are that the sensor data represent the seasonal vegetation signal in a meaningful way, and that the underlying vegetation variation is smooth. A number of processing steps are taken to transform the noisy signals into smooth seasonal curves, including fitting asymmetric Gaussian or double logistic functions, or smoothing the data using a modified Savitzky-Golay filter. TIMESAT can adapt to the upper envelope of the data, accounting for negatively biased noise, and can take missing data and quality flags into account. The software enables the extraction of seasonality parameters, like the beginning and end of the growing season, its length, integrated values, etc. TIMESAT has been used in a large number of applied studies for phenology parameter extraction, data smoothing, and general data quality improvement. To enable efficient analysis of future Earth Observation data sets, developments of TIMESAT are directed towards processing of high-spatial resolution data from e.g. Landsat and Sentinel-2, and use of spatio-temporal data processing methods.

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7.1 Introduction

Satellite-derived time-series data help us understand interactions of terrestrial vegetation dynamics with climate and the carbon cycle, and their trends over time (Keenan et al. 2014). Using efficient processing methods for analyzing existing remotely sensed time-series data is important for monitoring and mapping vegetation dynamics, thereby contributing to improved understanding of the global climate system. We will in this chapter present and describe one available tool, named TIMESAT, for processing time-series of satellite sensor data to enable meaningful data extraction for modeling vegetation dynamics.

The first time-series of satellite imagery for studies of dynamic Earth processes were made available from weather satellites. It was a series of satellites launched by the American National Oceanic Administration (NOAA) that generated daily data covering the entire Earth, and enabled the generation of global near-real time vegetation data. The first of these weather satellites to have bands suitable for vegetation mapping was NOAA-6, carrying an improved Advanced Very High Resolution Radiometer (AVHRR) sensor (Zhu et al. 2012). Though the sensor generated data at coarse spatial resolution (approx. 1×1 km resampled into a 4×4 km global product) the value of the data for global vegetation monitoring soon became evident. A series of data products based on the Normalized Difference Vegetation Index (NDVI), computed from the NOAA channels 1 and 2, were developed and were used for studying the temporal dynamics of global land vegetation (Justice et al. 1985; Townshend and Justice 1986). These were the NOAA Pathfinder data set (James and Kalluri 1994), the University of Maryland GIMMS data set (Tucker et al. 2005), and the recent, improved GIMMS (Global Inventory Modeling and Mapping Studies) NDVI(3 g) data set (Jiang et al. 2013). These data sets contain global images of NDVI from 1981 onwards at a time step of 10–15 days and a spatial resolution of ca 8×8 km. This temporal and spatial resolution is adequate for studying seasonal and interannual dynamics of vegetation biomes. Hence, several studies from the mid-1980’s and onwards have demonstrated how the information can be used for better understanding of vegetation dynamics as well as aiding land cover classifications (Defries and Townshend 1994; Running et al. 1994). In parallel, the increasing supply of high-spatial resolution data from sensors with 10–30 m resolution (e.g. Landsat and SPOT), and later on the development of satellites generating data at meter resolution (e.g. IKONOS, Quickbird, and Worldview), led to much of the technical development focusing on methods for classifying and quantifying high-resolution data. Hence, the development of time-series methodology in remote sensing was initially slow. However, it expanded quickly towards the beginning of the 2000’s with the need to process large volumes of time-series data from the Terra and Aqua MODIS (Advanced Very High Resolution Radiometer) sensors at 250 m spatial resolution.

The interest in developing the TIMESAT software package arose from a need to manage time-series data in remote sensing in order to help tackle problems related to global change and monitoring of vegetation resources. The research community was interested in solving a range of questions related to time-series: is vegetation in the world's drylands changing; can satellite data be used for issuing early warnings of drought and famine; how does NDVI respond to changes in environmental driving forces such as rainfall and temperature; can satellites be used for monitoring carbon uptake from the vegetation; are growing seasons changing; and how does vegetation respond to climate change? In fact, these and many other related questions have been the focus of a large body of research during the last 30–40 years. TIMESAT is just one of many approaches for data processing and extraction of phenological information from Earth observation time-series data.

The background, theory and some future issues related to TIMESAT are described in the remaining sections.

7.2 Handling Remotely Sensed Time-Series Data – Assumptions and Some General Problems

The study of vegetation seasonality from space is based on two fundamental assumptions. The first assumption is that the optical data correctly model biophysical vegetation properties (such as leaf area index (LAI), green biomass, or fractional absorbed photosynthetically active radiation (FAPAR)). Unfortunately this assumption is not perfectly satisfied. It is true that many of the commonly used vegetation indices are empirically related to biophysical vegetation properties, but they are also affected by several other processes and disturbances. For example, even when ignoring the effects of clouds, angular effects and the atmosphere, the popular vegetation indices NDVI and Enhanced Vegetation Index (EVI) do not only respond to vegetation variations, but are both very sensitive to e.g. snow or moisture-induced background variations (Huete et al. 2002). Sensor degradation and drift in satellite overpass times (particularly evident with the NOAA satellites) are other examples of factors affecting the data reliability. All these influences cause ambiguity in the interpretation of the signal, affecting the information value and our ability to interpret the extracted seasonality data.

The second assumption is that the temporal signal from the vegetation is smooth. The canopy leaf mass, and the bulk of pigmentation and leaf water strongly dominate the optical signal from vegetation; these all tend to vary relatively consistently with time in a seasonal pattern. The variation can be slow (e.g. coniferous evergreen forest), or rapid (e.g. semi-arid grasslands), however it is not random. On the other hand, some short-term variations do occur in vegetation, e.g. due to light saturation and plant stress, which may lead to short-term variations in chlorophyll fluorescence that adds to the apparent reflectance. Though this addition is generally small for broad wavelength bands it may add substantially to certain wavelengths; up to 10–25 % at 685 nm and 2–6 % at 740 nm (Campbell et al. 2008). Also reflectance at 631 nm can change rapidly with variations in photosynthetic radiation-use efficiency (Gamon et al. 1997). Naturally, also some vegetation disturbances, caused by insect infestations, storms, and fires, can lead to rapid decline in canopy foliage which affects the reflectance. Overall, however, the seasonal canopy signal tends to change smoothly in a seasonal perspective, particularly in comparison with the many disturbing factors that may change rapidly from image to image: the atmosphere, clouds, angular variations due to different viewing and illumination angles, and geometric inaccuracies. Figure 7.1 shows daily MODIS NDVI data for 3 years from a coniferous forest site in southern Sweden, illustrating the noise in these data. The data in Fig. 7.1a seem to be more or less fully made up of noise, and the seasonal variation is quite difficult to discern.

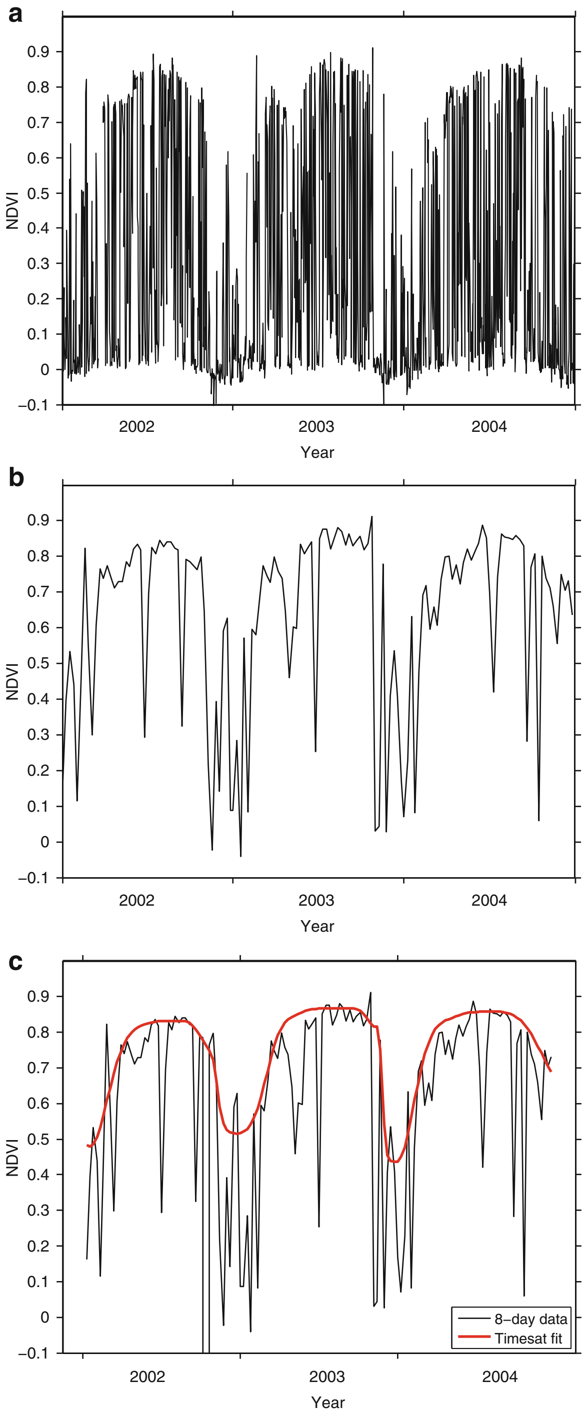
To transform the noisy data into an understandable signal, a number of processing steps are necessary. These steps may include removing cloud interference by applying cloud masks (often based on thresholds in visible and thermal wavelengths), removing atmospheric absorption and scattering effects, and applying methods for correcting bi-directional illumination and viewing effects in the data. Employing a perfect set of physically based methods would be the ideal way of generating correct time-series data. However, with thousands of images having to be corrected it is usually necessary from a practical point of view to clean up the data using simple and rapid methods. One of these methods is maximum-value compositing, in which data over a short time-period (8–15 days) are scanned, and the maximum NDVI value retained to represent the time period (Holben 1986). The method has proven to be surprisingly effective in reducing noise in NDVI data, since cloud, atmospheric absorption, background color variations, etc., tend to lower the NDVI values. The result of 8-day maximum-value compositing applied to the coniferous MODIS data is seen in Fig. 7.1b.

A further way of managing noise is to use the quality flags, e.g. MODIS QA (MODIS Quality assessment), which are delivered with many remotely sensed products today, and which indicate the reliability of each observation. Though these flags are useful for removing doubtful data they are not easily applied in a more quantitative sense for improving the quality of the time-series.

Returning to Fig. 7.1, it can be seen from Fig. 7.1b that the maximum-value compositing has not been able to remove all the noise. Several observations of doubtful quality remain, and they have a clear negative bias. Thus, in most cases it is necessary to smooth the time-series data further using filters or other smoothing functions before extracting seasonality data. In doing so, the methods should take the negative noise bias into account, and should be able to handle missing data. Figure 7.1c shows the result of applying a smoothing function in the TIMESAT software package. This has resulted in a smooth curve that fits to the upper envelope of the data points. More information about data smoothing is given in the sections below.

Once a smooth data set has been generated it is possible to extract growing seasons and phenological parameters. Since vegetation indices are affected by a range of different processes (compare discussion above), their biophysical meaning is sometimes vague, and extraction of phenological parameters becomes somewhat subjective. Given this uncertainty it is not possible to define universal thresholds for defining the beginning and end of growing seasons. A further complication is that

Fig. 7.1 (**a**) Daily NDVI data from MODIS for a mixed coniferous forest pixel in central Sweden; (**b**) 8-day maximum-value composite data for the same pixel; (**c**) smooth representation of the 8-day data from the same pixel using an upper-envelope weighted asymmetric Gaussian fit in TIMESAT



the time periods of most rapid shift in the sensed signal often coincide with meteorological changes. In tropical drylands, for example, the rainy season marks the onset of the growing season, but also brings cloudiness that affects signal quality; in cold areas the period of snow melt overlaps with the leaf development phase. Additionally, the understorey vegetation in many climate zones develops before the tree canopies, making it hard to use remotely sensed data for distinguishing the two processes.

Another complicating factor when mapping growing seasons is that, though the seasons normally follow an annual rhythm, they do not necessarily occur within single calendar years. In the Southern Hemisphere the growing season may begin in one year and end the year after. Although we are used to describing annually repeating phenomena, like agricultural production, with statistics for each calendar year, vegetation growing seasons are not always well suited to this. In addition, many areas of the world experience two (sometimes even three) growing seasons per year. Hence, phenological statistics should preferably not be reported per year, but per season (relative to a fixed starting date).

Last, but not least, it is necessary to consider the huge, and rapidly growing, storages of digital Earth Observation data available. For example, processing the whole of Africa at 250×250 m resolution using MODIS 8-day data for the 2000–2013 period means that roughly 523.6 billion points have to be analyzed; it is obviously necessary to use fast and reliable computing algorithms when estimating seasonality.

7.3 Processing Considerations and Common Methods

The problem of deriving precise seasonal information consists of three parts: (1) using remotely sensed data that correctly represent vegetation phenology, thereby fulfilling the first assumption above; (2) employing a smoothing method that, following assumption two above, accurately filters noise without altering the general shape of the seasonal curve; and (3) defining parameters of the growing season.

1. Regarding remotely sensed data to be used, maximum-value composites of vegetation indices like the NDVI, and in later years the EVI, have been the most commonly used. These are normally derived from top-of-atmosphere reflectance data from the MODIS or AVHRR sensors. However, there is reason also to focus on other data sets. In particular, higher-order products developed from the original satellite reflectances are important, such as the MODIS NBAR (MODIS Nadir Bidirectional Reflectance Distribution Function Adjusted Reflectance) and the MODIS albedo products, in which data have been corrected for bi-directional effects. Also other derived products with a clear biophysical meaning (e.g. LAI or FAPAR) make it easier to interpret the resulting seasonal parameters from a vegetation phenology point of view (provided that the

products accurately model these parameters). The development of new and improved biophysically relevant data sets is a highly active and relevant research field. For example, a recently developed plant phenology index (PPI), which is linearly related to green LAI, has strong potential for more accurately mapping of vegetation phenology than the traditionally used indices (Jin and Eklundh 2014).

2. A variety of smoothing methods have been developed and tested. Fourier series were among the first methods to be tested for extracting seasonality information from remotely sensed imagery (van Dijk et al. 1987; Menenti et al. 1993; Olsson and Eklundh 1994). The parameters of the harmonic functions contain useful information about the timing of seasons and the number of growing seasons per year. However, the method is inflexible when modeling individual years; Fourier series are better suited to data with less interannual variability than is often seen for remotely sensed time-series data. Another line of development is the use of various temporal filters for smoothing the time-series data. One early method was the best index slope extraction (BISE) (Viovy et al. 1992). In this method the upper envelope of the time-series is extracted by connecting the upper-most data points in a sliding window. The method is based on the principle of minimizing noise by consistently selecting the highest NDVI values; however in doing so it neglects the fact that also positive noise, e.g. due to angular effects, is present in the data. Also other smoothing filters have been used, e.g. the 4352H filter (van Dijk et al. 1987) and median filters (Reed et al. 1994). More recently various functions have been fitted to data: asymmetric Gaussian functions (Jönsson and Eklundh 2002), logistic functions (Zhang et al. 2003; Jönsson and Eklundh 2004; Fisher et al. 2006), and spline functions (Bradley et al. 2007; Hermance et al. 2007). Also wavelet transforms have been shown to be useful (Sakamoto et al. 2005; Lu et al. 2007; Campos and Di Bella 2012). In general, the choice of smoothing method is related to the type of input data and the desired result. If data are relatively smooth and the aim is to preserve variations on the seasonal curve, local filtering methods can be employed. If data are very noisy it might be necessary to enforce a general seasonal shape on the data by employing a more global type of function (e.g. asymmetric Gaussian or logistic function).
3. Regarding the extraction of phenological parameters, some different methods have been used. Most are based on absolute or relative thresholds of the seasonal amplitude. Others are purely mathematical parameters (inflexion points or derivatives of different order). Common for all these methods is that they seldom are based on any biological or physical understanding of the phenological process, but rather on empirical relationships. A more elaborate method, based on fitting shape models to smoothed data, yielded high fidelity for crop phenological parameters (Sakamoto et al. 2010). The choice of method cannot be separated from the type of input data or the fitting method used. For example, methods based on derivatives should not be used with data that are not very smooth.

It can be questioned whether it is possible to define a single set of smoothing and parameter extraction methods that will work across all different ecosystems and with all different types of remotely sensed data. White et al. (2009) made an extensive study including ten different methods for estimating spring phenology across the United States, concluding that the different methods did not behave consistently, and that, in their study, there was no rational basis for selecting one method over the other. Considerable inter-method differences were also documented by Cong et al. (2013). It is likely that bias and random errors due to cloud interference lead to temporally and spatially varying performance of different smoothing and filtering methods (Chen et al. 2013). Furthermore, phenological parameters are generally difficult to assess, as ground data have large variability and are often observed over small areas. Hence, it is in general very difficult to assess the reliability of processing methods; achieving smoothness is one thing, accurately depicting true vegetation variations is not necessarily the same. Intermediate-scale canopy data from phenocams and near-ground spectral sensors serve an important means of understanding and validating satellite-derived phenological parameters (Richardson et al. 2007; Eklundh et al. 2011; Hufkens et al. 2012).

7.4 The TIMESAT Approach

7.4.1 Processing Principles

TIMESAT has been developed with flexibility in mind, and is thus not oriented towards any specific data source or format. Hence, users are required to pre-process data before the actual TIMESAT processing can begin. Depending on the data source different preparation steps may be necessary, e.g. converting image data into the binary formats used in TIMESAT, organizing images in time stacks with equal time step, preparing lists of file names, and converting quality information into rank units that can be processed by TIMESAT. The actual TIMESAT processing consists of a series of steps: (1) computing the trend in the data using the Seasonal Trend decomposition by Loess (STL) method (Cleveland et al. 1990); (2) pre-filtering of data, in which extreme outliers and pixels with too few data points are removed; (3) computing a coarse seasonal fit to de-trended data based on sinusoidal harmonics to determine the number and approximate location of growing seasons; (4) smoothing the data using either of three different methods: adaptive Savitzky-Golay filter, asymmetric Gaussian or double logistic functions; (5) computing seasonal parameters for each extracted season; and (6) generating output data in the form of single-pixel data or images. The output includes smoothed data for each time step, and seasonality parameters for each identified growing season. The processing is controlled from a graphical user interface in which the necessary settings are determined based on visual control of sample time-series from the image data stack. When suitable settings have been determined, the full image data

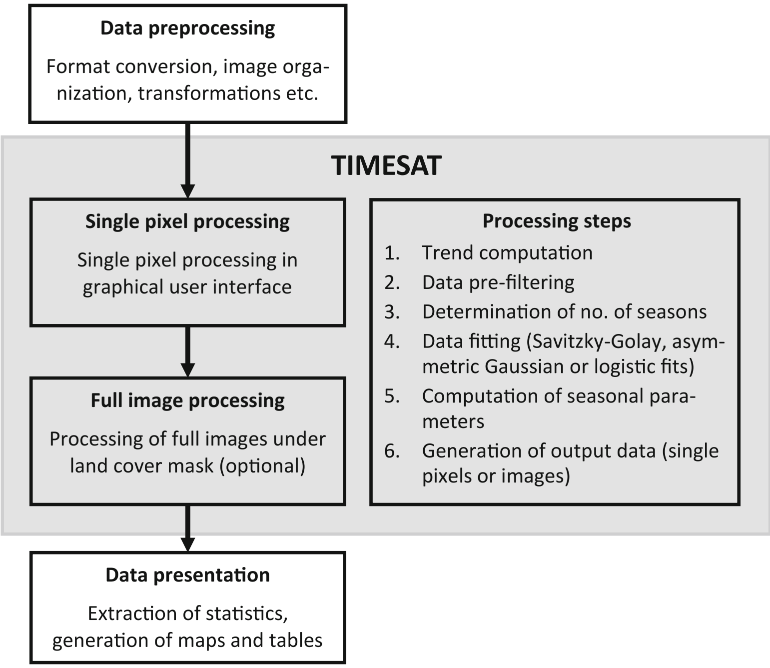


Fig. 7.2 Principle of TIMESAT work flow. The *white boxes* show tasks done outside of TIMESAT, whereas the *grey boxes* show functionality in TIMESAT. The processing steps 1–6 are done for single pixels as well as for full images, and are further described in the text

can be processed. A summary of the processing steps is presented in Fig. 7.2; we also refer to the TIMESAT manual for more detailed information (Eklundh and Jönsson 2012).

All data values to be processed have an associated weight which can be derived from product quality flag data or from STL. In the subsequent processing the weights can be modified if the user wishes to fit data to the upper envelope. This is done by reducing the weights of data points below the fitted functions, in up to a maximum of three iterations. All data fitting is done using weighted least squares, which means that short data gaps are handled without interpolation.

The first smoothing method implemented in TIMESAT was based on asymmetric Gaussian functions (Jönsson and Eklundh 2002). The method consists of seasonal functions fitted piecewise to the data and merged to a global continuous data series. Subsequently, double logistic functions and Savitzky-Golay filtering were added to TIMESAT (Jönsson and Eklundh 2004). An example of the results of running the three smoothing methods in TIMESAT are shown in Fig. 7.3. It can be seen that the Gaussian and logistic functions are very smooth and global in nature. They are most useful when data are very noisy and the user wishes to enforce a bell-shaped pattern on the data. The Gaussian functions adapt somewhat better than the logistic functions to flat peaks, otherwise the two methods are very similar. The Savitzky-Golay method, on the other hand, filters the data and follows local

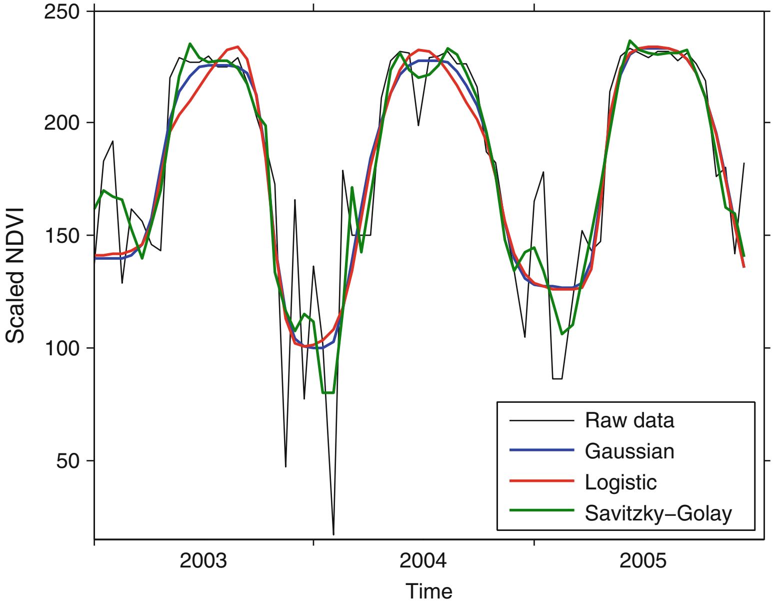


Fig. 7.3 TIMESAT fits to MODIS 16-day NDVI data from a deciduous forest in S. Sweden

variations in the seasonal curve more closely. The Savitzky-Golay implementation in TIMESAT is adaptive in that it iteratively tightens the search window in order to capture very rapid increase or decrease in the data. This is useful when monitoring e.g. semi-arid grasslands, where the ground can green-up in the course of a few days, leading to a very rapid increase in vegetation index data. Smoothing very noisy data requires an increased search window, which in turn can produce some artefacts. Therefore, Savitzky-Golay filtering is best used with data that is not extremely noisy.

Hird and McDermid (2009) showed that the methods in TIMESAT have good performance, balancing the ability to reduce noise and maintain the signal integrity.

Several of the methods in TIMESAT require the user to make individual settings, e.g. controlling the degree of smoothing or the envelope fitting. In small areas it might be enough to do this once, but for large areas with diverse land cover it might be necessary to define different settings for different areas. In order to maintain flexibility it is possible to store several groups of settings, and then apply these to different areas in the image, controlled by e.g. a land cover map.

After smoothing the data, TIMESAT proceeds to compute phenological parameters. The user determines thresholds for defining the start and end of seasons (absolute values or fractions of the amplitude), and the following parameters are then computed for each season: times of start and end of season; length of season; base level; time of midpoint; maximum value; amplitude; rates of increase and decrease; and large and small integrals. Examples of two phenological parameters, mapped for West Africa from AVHRR data, are shown in Fig. 7.4. The definition

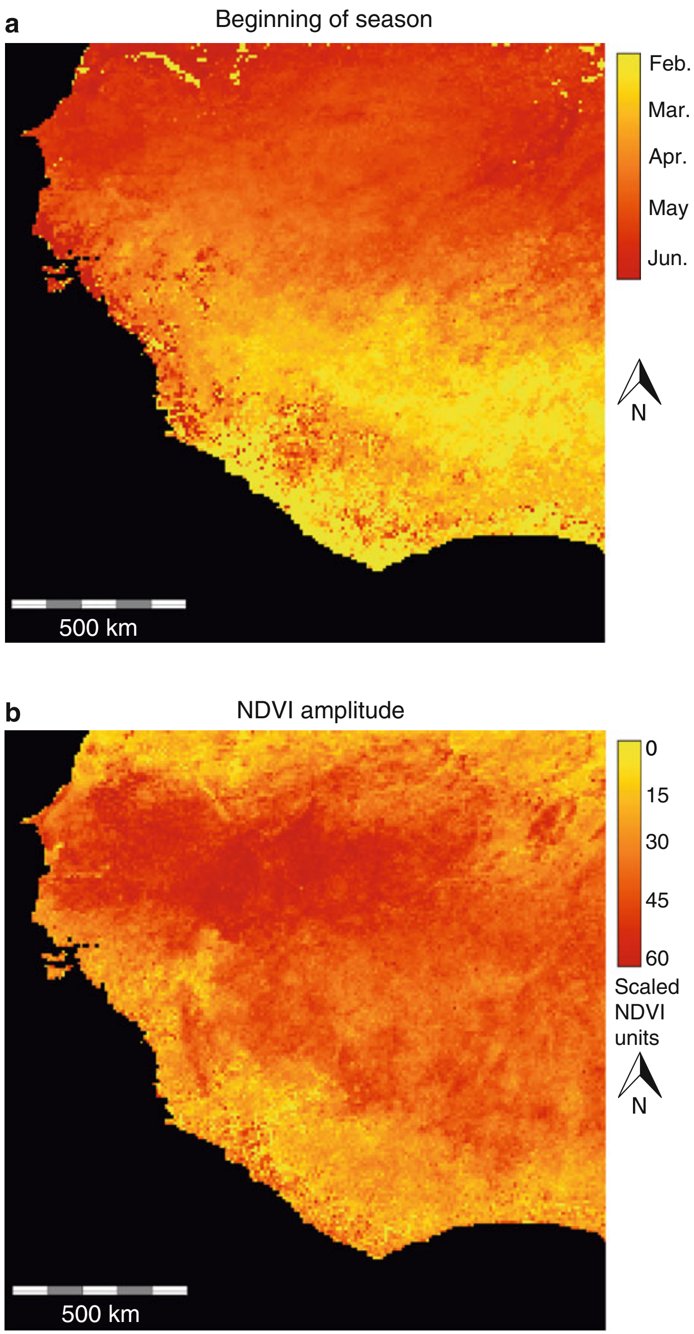


Fig. 7.4 TIMESAT seasonality parameters computed from a Gaussian-smoothed NOAA AVHRR data set over West Africa 1999; (**a**) start of season; (**b**) amplitude of season

and selection of phenological parameters in TIMESAT is somewhat arbitrary. Though several studies have shown that many of them make sense from an ecosystem perspective and are empirically related to inter-seasonal variations in climatic driving forces, more research is clearly needed to more precisely establish their actual value and ecological meaning.

7.4.2 Applications of TIMESAT

TIMESAT has been used in a wide variety of applications since the first version was written in the early 2000's. Our own interest was initially focused on mapping of environmental changes in the African Sahel using the AVHRR data records from 1982 till today. Some of the first evidence of the increasing greenness in the Sahel, from the droughts in the 1980's, was presented by Eklundh and Olsson (2003); this increase was subsequently linked to variations in climate drivers (Hickler et al. 2005; Olsson et al. 2005; Seaquist et al. 2009). In these studies TIMESAT was primarily used for computing seasonal amplitudes and integrals of NDVI. However, Heumann et al. (2007) also studied the changes in other phenological parameters in the Sahel, like the start and end of the growing seasons. Other phenology studies using TIMESAT include those by Beck et al. (2007), who mapped high-latitude forest phenology in Fennoscandia and the Kola Peninsula, O'Connor et al. (2012), who mapped spatio-temporal patterns of growing seasons on Ireland, and Boyd et al. (2011), who mapped phenology in S. England using the MERIS terrestrial chlorophyll index (MTCI; Dash and Curran 2007). Other case studies have been conducted in the US (Zhao et al. 2013), Europe (Han et al. 2013), South America (van Leeuwen et al. 2013), and in Arctic areas (Zeng et al. 2013). Jönsson et al. (2010) used TIMESAT while demonstrating the difficulties in extracting phenological parameters from MODIS NDVI data over boreal coniferous forests. Also disturbances in phenological patterns due to insect infestations have been analyzed (Eklundh et al. 2009; Olsson et al. 2012; Buma et al. 2013).

TIMESAT has been used in several studies on vegetation classification and phenological characterization of ecosystems (Tottrup et al. 2007; Clark et al. 2010; van Leeuwen et al. 2010; Wessels et al. 2011; Zhang et al. 2013a; Leinenkugel et al. 2013). It has furthermore been used for fire and fire risk modeling (Verbesselt et al. 2006; Veraverbeke et al. 2010; Le Page et al. 2010), and for investigating the impact of vegetation variability on predictability of a coupled land-atmosphere model (Weiss et al. 2012). In agriculture, TIMESAT has been used for estimation of sow dates (Lobell et al. 2013) and for mapping of abandoned cropping fields (Alcantara et al. 2012).

TIMESAT has been used for estimating diurnal air temperature from MSG SEVIRI data (Stisen et al. 2007), to study expansion of the thermal growing season and associated change in the biospheric carbon uptake (Barichivich et al. 2012), and to study the impact of extreme precipitation on reduction of terrestrial ecosystem production (Zhang et al. 2013b).

An important application field of TIMESAT is data smoothing to improve signal quality: Improved MODIS data quality has, when calibrating models with eddy-covariance flux tower data and other environmental data, led to generally better possibilities to estimate carbon fluxes (Olofsson and Eklundh 2007; Olofsson et al. 2007, 2008; Sjöström et al. 2009, 2011; Schubert et al. 2010, 2012; Tang et al. 2013). TIMESAT has also been used for data quality improvement with MODIS and AVHRR satellite products (Fensholt and Proud 2012), and for smoothing of GIMMS NDVI(3G) data for high northern latitudes (Barichivich et al. 2013). Data quality improvement is also the reason for using TIMESAT in an improved reprocessed version of the global MODIS LAI data set for land surface and climate modeling (Yuan et al. 2011).

7.5 Future Perspectives

We currently have over three decades of global AVHRR data, and over one decade of MODIS data from the Terra and Aqua satellites available. New satellites will continue to extend these time series into the future. As the data records grow, using them for studying impacts of climate and human action on the environment will be possible with increased confidence. This will increase the demand for the data, and call for further improving the methods for time-series data management and for exploiting the data, e.g. to extract linear and non-linear trends (Verbesselt et al. 2010; Jamali et al. 2014, 2015).

Earth observation is now taking an important step into a new era, with growing archives of time-series data at high spatial resolution. The release of the Landsat archive into the open domain has opened up for a range of new applications (Wulder et al. 2012); several new methods for exploiting these data, particularly for forest monitoring, are being developed (e.g. Huang et al. 2010; Kennedy et al. 2010; Zhu et al. 2012).

The next leap will be taken with the ESA Sentinel-2 satellites, to be launched in 2015 and 2017, generating Earth observation data at 10 m resolution with a 5-day interval. This will present both enormous opportunities and challenges. First, the high spatial resolution will mean that data validation against field measurements will be much improved compared with the 250–1,000 m data presently used. At this high resolution it will be possible to monitor vegetation at the scale of individual forest stands rather than at the ecosystem scale. Second, the high time resolution will mean that it will be possible to model seasonality more accurately than is possible with Landsat, SPOT or the other existing high-resolution sensors. The nature of data will present many new challenges, such as irregular time steps; hence new methods for gap-filling, smoothing and data fusion will have to be explored. Modification of TIMESAT to enable analysis of high-resolution data from Sentinel-2 is ongoing (Eklundh et al. 2012). Third, the new satellites will generate enormous volumes of data, calling for high-performance computing methods for processing all the data. A version of TIMESAT for parallel computing has been developed, showing almost linear scaling with the number of processors.

A further line of development is the integration of spatial and temporal dimensions. We have previously seen that incorporating the spatial domain will increase the significance in estimation of trend parameters across time (Bolin et al. 2009). It is likely that noise in time-series data can be reduced when estimating seasonal trajectories by extending the analysis into the spatial domain. Hence, we are currently exploring spline based methods in TIMESAT that can smooth the data across both time and space (Eklundh and Jönsson 2013).

Remote sensing science has come a long way towards extraction of environmentally meaningful time-series data during the last 10–20 years. With the new data types being released, and new and efficient processing methods being developed, Earth observation is now being accepted as an established and accurate tool for analyzing the Earth and its changes.

TIMESAT can freely be downloaded from http://www.nateko.lu.se/TIMESAT.

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