A time series for monitoring vegetation activity and phenology at 10-daily time steps covering large parts of South America

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It is widely accepted that natural resources should only be sustainably exploited and utilized to effectively preserve our planet for future generations. To better manage the natural resources, and to better understand the closely linked Earth systems, the concept of Digital Earth has been strongly promoted since US Vice President Al Gore’s speech in 1998. One core element of Digital Earth is the use and integration of remote sensing data. Only satellite imagery can cover the entire globe repeatedly at a sufficient high-spatial resolution to map changes in land cover and land use, but also to detect more subtle changes related for instance to climate change. To uncover global change effects on vegetation activity and phenology, it is important to establish high quality time series characterizing the past situation against which the current state can be compared. With the present study we describe a time series of vegetation activity at 10-daily time steps between 1998 and 2008 covering large parts of South America at 1 km spatial resolution. Particular emphasis was put on noise removal. Only carefully filtered time series of vegetation indices can be used as a benchmark and for studying vegetation dynamics at a continental scale. Without temporal smoothing, subtle spatio-temporal patterns in vegetation composition, density and phenology would be hidden by atmospheric noise and undetected clouds. Such noise is immanent in data that have undergone solely a maximum value compositing. Within the present study, the Whittaker smoother (WS) was applied to a SPOT VGT time series. The WS balances the fidelity to the observations with the roughness of the smoothed curve. The algorithm is extremely fast, gives continuous control over smoothness with only one parameter, and interpolates automatically. The filtering efficiently removed the negatively biased noise present in the original data, while preserving the overall shape of the curves showing vegetation growth and development. Geostatistical variogram analysis revealed a significantly increased signal-to-noise ratio compared to the raw data. Analysis of the data also revealed spatially consistent key phenological markers. Extracted seasonality parameters followed a clear meridional trend. Compared to the unfiltered data, the filtered time series increased the separability of various land cover classes. It is thus expected that the data set holds great potential for environmental and vegetation related studies within the frame of Digital Earth.

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1. Introduction

As pointed out by Shupeng and van Genderen (2008) the Digital Earth concept is now well established and widely adopted internationally. This acceptance reflects the fact that effective actions against the unsustainable use of natural resources can only be conducted if we better understand and visualize the Earth (Guo et al. 2010). At a coarse spatial resolution (~1 km) remotely sensed vegetation indices are acquired and have been used since the 1980’s to characterize the state of the vegetation. Generally, vegetation indices combine remotely sensed reflectances in the red ($\rho_{\text{red}}$) and near infrared ($\rho_{\text{nir}}$) to derive a measure of vegetation activity or density. A prominent example is the NDVI ($\text{NDVI} = (\rho_{\text{nir}} - \rho_{\text{red}})/(\rho_{\text{nir}} + \rho_{\text{red}})$) which is at the heart of many environmental and vegetation related studies. Prominent applications of vegetation indices include the measurement of phenological variability (Reed et al. 1994, Stöckli and Vidale 2004), the establishment of continental phenological models (White et al. 1997), and the unraveling of teleconnections between climatic anomaly indices and vegetation response (Anyamba and Eastman 1996, Kogan 2000). In these cases the phasing of the signal is the main variable being analyzed. In other studies, the amplitude of the signal is the main concern. Such studies include the modeling of spatio-temporal patterns of vegetation activity (Yu et al. 2003, Martínez and Gilabert 2009) and the assessment of global and climate change (Tucker et al. 2001, Zhou et al. 2001). Time series of NDVI were also used for the mapping of plant functional types, phenoregions, and land use categories (Azzali and Menenti 2000, Paruelo et al. 2001), for ecological research and wildlife distribution modeling (Kerr and Ostrovsky 2003, Pettorelli et al. 2005), and as support to biodiversity mapping (Hurlbert and Haskell 2003, Coops et al. 2009). In an operational context, NDVI time series are used for agricultural monitoring and yield predictions (Fuller 1998, Zhang et al. 2005), and for drought assessments (McVicar and Jupp 1998, Ji and Peters 2003).

Obviously, the mentioned applications rely heavily on the reliability and internal consistency of the analyzed time series. However, the quality of remotely sensed NDVI time series is known to be affected by atmospheric noise and undetected clouds yielding negatively biased noise (Goward et al. 1991). To compensate for this bias, the daily NDVI observations are usually subjected to a maximum value compositing (MVC) process (Holben 1986). This method reduces a considerable amount of noise that is present in the images and eliminates sensor-related artifacts such as line dropout. With MVC, only the highest NDVI value in a predefined compositing period (typically: 10 days) is retained. This results in fewer but more reliable NDVI values representing the time series.

Albeit useful, MVC reduces only the main perturbations. Further filtering is usually required to obtain meaningful and smooth NDVI profiles. This is a quite complicated task, as the amount of noise resulting from (undetected) clouds and atmospheric turbidity is highly variable in space and time (Chen et al. 2004, Beck et al. 2006). Additional white noise is introduced by BRDF and soil background effects. For example, a vegetated surface with a dark (wet) soil background will show a higher NDVI as compared to a similar dense canopy having a bright (dry) soil. As
the amount of vegetation ‘seen’ by a sensor increases with increasing view angle, the
NDVI will increase with more oblique views (BRDF effect). Thus this kind of noise
will be characterized by a zero mean. It will not introduce a (negatively) biased
NDVI observation as discussed for the atmospheric noise.

For noise removal, a number of smoothing techniques have been proposed (Table 1).
For each of the methods serious shortcomings have been noted. Valuable overviews are
given, for example in Chen et al. (2004), Jönsson and Eklundh (2004), and Beck
et al. (2006). In a recent study, Hird and McDermid (2009) subjected six widely used
filtering techniques to a model-based empirical comparison. The authors found a
general superiority of the double logistic (Beck et al. 2006) and the asymmetric
Gaussian (Jönsson and Eklundh 2004) function-fitting methods over four alternative
techniques including Savitzky–Golay (Chen et al. 2004), 4253H twice (Velleman 1980),
and Mean Value Iteration (Ma and Verostraete 2006). However, their analysis also
demonstrated the strong influence of noise level, strength, and bias on technique
performance. Furthermore, a considerable influence of metric choice and biogeogra-
phical region on the performance of the six candidate techniques was noticed.
Additional concerns relate to the computational requirements (e.g. processing speed,
memory requirements, and handling of missing values), to edge-effects (important for
real-time applications), and to the parameterization load (and hence required skills of
the user), to mention only a few additional problems. This explains why until now no
general consensus has been reached as to which approach is the most favorable.

For well balancing the fidelity to the observations with the roughness of the
smoothed curve in an automatic and computationally fast way, the Whittaker
smoother (WS) was selected for the current study (Eilers 2003, Atzberger and Eilers
2010). The WS fits a discrete series to discrete data. An iterative procedure is used to
down-weight negatively biased and unreliable observations, leading to a smooth
curve that approaches the upper envelope of the data, and thus the most reliable
observations. The algorithm is extremely fast and interpolates automatically missing
data. It gives continuous control over smoothness with only one parameter. The

Table 1. Prominent techniques for smoothing remotely sensed time series of vegetation
indices.

<table>
<thead>
<tr>
<th>Type of filter</th>
<th>Prominent examples</th>
</tr>
</thead>
<tbody>
<tr>
<td>Harmonic series, e.g. fast and discrete Fourier transform</td>
<td>Roerink et al. (2000), McClory and Lucht (2004), Bradley et al. (2007), Hermance (2007)</td>
</tr>
<tr>
<td>Double logistic</td>
<td>Zhang et al. (2003), Beck et al. (2006)</td>
</tr>
<tr>
<td>Wavelets</td>
<td>Li and Kafatos (2000), Sakamoto et al. (2005)</td>
</tr>
<tr>
<td>Best Index Slope Extraction</td>
<td>Viovy et al. (1992), Lovell and Graetz (2001)</td>
</tr>
<tr>
<td>Weighted least squares windowed regression</td>
<td>Swets et al. (1999)</td>
</tr>
<tr>
<td>Running medians</td>
<td>Velleman (1980)</td>
</tr>
<tr>
<td>Mean value iteration</td>
<td>Ma and Verostraete (2006)</td>
</tr>
<tr>
<td>Mean compositing</td>
<td>Vancutsem et al. (2007)</td>
</tr>
<tr>
<td>Whittaker smoother</td>
<td>Atzberger and Eilers (2010)</td>
</tr>
</tbody>
</table>
smoothness parameter is estimated from the data itself eliminating possible problems related to the skills of the operator. This makes the WS a good choice for filtering coarse resolution time series of vegetation indices to be included in Digital Earth databases.

The paper starts with a short description of the SPOT VGT input data. Next, the WS is presented together with geostatistical procedures for assessing the signal-to-noise ratio (SNR) of the images (Chappell et al. 2001). In the last section, the filtered time series is characterized both in terms of image quality and usefulness for vegetation related studies. For this purpose a few illustrated examples will be given. Together this should give the reader an impression of: (a) existing data sets for global change monitoring at large scales; and (b) demonstrate the importance (and techniques) for providing image-derived quality indicators to be used as metadata descriptors in Digital Earth repositories.

2. Data

2.1. Study area

The region embraced by the data set is situated between 0° S 70° W (top left) and 40° S 35° W (bottom right). It covers an area of approximately 18 Mio. km² (image size: 4400 × 4000) and includes Brazil, Argentina, Uruguay, Paraguay, and Bolivia (Figure 1). Climatic conditions within the area are highly variable (Rao and Hada 1990, Kogan 2000) leading to contrasting vegetation types ranging from tropical evergreen moist forests to xeric and montane shrublands.

The key eco-regions of the area are shown in Figure 1a according to Olson et al. (2001). The distribution of the main land cover types is depicted in Figure 1b based on the GLC2000 land cover map (Bartholomé and Belward 2005). Further maps show the IPCC cloud climatology (30 yr; Mitchell and Jones 2005) for the month of January (austral summer) and July (austral winter) (Figure 1c and 1d). The last two maps were included to provide the reader with an impression of atmospheric related problems to be expected in the region of interest.

2.2. Remote sensing and ancillary data

The time series consists of 10-day MVC-NDVI images from SPOT VGT covering the time period from April 1998 to December 2008. The images were pre-processed by the Flemish Institute for Technological Research (VITO) using a consistent processing algorithm including geometric, radiometric, and atmospheric corrections. After smoothing, the 10 annual cycles between July 1998 and June 2008 were retained (i.e. 360 image layers).

The VGT data were acquired by two identical instruments onboard SPOT 4 and 5. The sensor provides global observations of the surface from a sun-synchronous orbit at 822 km altitude, with a revisit period of 26 days and an equatorial crossing time at 10:30. Due to the large swath (101°, equivalent to 2200 km) an almost global daily coverage is provided. The instrumental concept relies on a linear array of CCD detectors providing a spatial resolution around 1 km with minimum variations for off-nadir pixel size thanks to the telecentric design of the optics. The stability of the platform, the accurate knowledge of its position and attitude together with the post-processing of the images allow to achieve a multi-temporal registration accuracy
The system and the corresponding products are described with more details in Maisongrande et al. (2004). For stratification purposes, the GLC2000 land cover map was used (Bartholomé and Belward 2005). The cloud climatology data (CRU; period 1969–1990) were downloaded from http://ipcc-data.org (Mitchell and Jones 2005). The processing and analysis was carried out using Matlab 7.5 (Mathworks 2007).

3. Methods

The WS is described in detail by Eilers (2003). A small toolbox of Matlab functions for Whittaker smoothing is available free of charge via the Internet at http://pubs.acs.org. For the present study the smoother was slightly modified to deal with

Figure 1. Characteristics of the region (South America) covered by the SPOT VGT time series: (a) major eco-regions (Olson et al. 2001); (b) broad land cover classes according to GLC2000 (Bartholomé and Belward 2005); (c) and (d) climatological cloud coverage (IPCC) for January and July, respectively (Mitchell and Jones 2005).
the negatively biased noise typical for NDVI time series. We will first describe the basic algorithm (3.1) followed by a short description of the necessary adaptations (3.2). The geostatistical measures used to evaluate the filter performance are described in the last part of this section (3.3). Amongst others, these measures allow to quantify the SNR of the produced data sets, which should be included in appropriate metadata descriptors. As mentioned by Shupeng and van Genderen (2008), only fully calibrated E.O. data sets permit a quantitative comparison of different regions on the globe.

3.1. The basic Whittaker smoother (WS)

The ‘Whittaker smoother’ (Whittaker 1923) is based on penalized least squares. It fits a discrete series to discrete data and puts a penalty on the roughness of the smooth curve. The algorithm is extremely fast, gives continuous control over smoothness with only one parameter, and interpolates automatically. It adapts well to boundaries and does not assume periodicity. Its fast cross-validation can be used for a self-acting choice of the smoothing parameter. The filter is well-known by the statistical community and widely used in biology. It has shown a high potential for filtering remotely sensed time series (Atzberger and Rembold 2009, Atzberger and Eilers 2010).

Suppose a noisy series $y$, sampled at equal distances (here, every 10 days) of length $m$ is given. The aim is to fit a smooth series $z$ to $y$. Hereby, two conflicting goals have to be balanced: (1) fidelity to the data; and (2) roughness of $z$. The smoother $z$ is, the more it will deviate from $y$. A balanced combination of the two goals is the sum ($Q$)

$$ Q = S + \kappa R $$

with

$$ S = \sum_i (y_i - z_i)^2 $$

$$ R = \sum_i ((z_i - z_{i-1}) - (z_{i-1} - z_{i-2}))^2 $$

The lack of fit to the data, $S$, is measured as the usual sum of squares of differences. The roughness of the smoothed curve, $R$, is expressed here as second order differences. The number $\kappa$ is chosen by the user and is called smoothing parameter.

The aim of penalized least squares is to find the series $z$ that minimizes $Q$. The larger the parameter $\kappa$, the stronger is the influence of $R$ on the goal $Q$ and the smoother will be $z$ (at the cost of the degradation of the fit).

In matrix notation we get a linear system of equations

$$ (I + \kappa D'D)z = y $$

where $I$ is the identity matrix and $D$ is a matrix with $m-2$ rows and $m$ columns where each row contains the pattern 1, $-2$, 1, shifted such that $d_{i,1} = 1$, $d_{i,1+1} = -2$ and $d_{i,1+2} = 1$ (all other elements of $D$ are 0).
One way of choosing a value for the smoothing parameter $k$ is tuning it until a visually pleasing result is obtained. Using cross-validation, a more objective choice can be made. The idea is to leave out each of the non-missing elements of $y$ in turn, smooth the remaining data and get a prediction $y_{-i}$ for the left out $y_i$. By repeating this for all $y_i$ we can compute the cross-validation standard error

$$s_{cv} = \sqrt{\frac{\sum (y_i - y_{-i})^2}{m}}$$  \hspace{1cm} (5)$$

To find the optimal value of $k$, its value is varied on a grid to search for a minimum of $s_{cv}$.

Remotely sensed time series may contain (large stretches of) missing data (e.g., cloud flags). The smoother can easily handle missing data. The missing elements of $y$ are simply set to an arbitrary value (e.g., $-99$), and a vector $w$ of weights is introduced, with $w_i = 0$ for missing observations and $w_i = 1$ for all other observations.

The system of equations (Equation (4)) changes to

$$(W + \kappa D'D)z = Wy$$  \hspace{1cm} (6)$$

where $W = \text{diag}(w)$, a diagonal matrix with $w$ on its diagonal.

At the positions where $y$ is missing, $z$ is automatically and smoothly interpolated. This feature can also be used as an easy device for smoothing and detailed interpolation (e.g. to a daily time step), as well as for extrapolations and forecasts.

### 3.2. Adaptation of the Whittaker smoother (WS) to remotely sensed time series with negatively biased noise

Similar to other techniques for reducing noise and constructing high-quality NDVI time-series, the proposed adaptations are based on two assumptions (Chen et al. 2004): (1) that the NDVI time-series follows an annual cycle of growth and decline as the index is primarily related to vegetation density; and (2) that clouds and poor atmospheric conditions depress NDVI values, requiring that sudden drops in NDVI, which are not compatible with the gradual process of vegetation change, are regarded as noise and will be removed.

In line with these two assumptions, the basic Whittaker algorithm was modified to fit the upper envelope of the data through an iterative process. The approach is illustrated in Figure 2 and can be applied to data sampled at different sampling intervals (e.g. from daily to monthly data) as well as to irregularly sampled data. There are no restrictions regarding the scaling of the data, the specific sensors, or the vegetation index to be filtered. This makes the filter an appealing candidate for smoothing remotely sensed time series to be included in the Digital Earth database.

In a first run (Figure 2a) the filter smoothes the observed time series (in gray) using the basic Whittaker algorithm (Equation (6)). Next (Figure 2b), all observed values (circles) that lie below the fitted curve (or that were missing/flagged values) are replaced by their fitted value. With the updated values (rectangles), the smoothing is repeated (Figure 2b; black line). For the final iteration, the values below the curve are again replaced by the curve values followed by a run of the smoother. The outcome of this third run is the final result (Figure 2c; black line). Depending on the selected
smoothing parameter \((k)\) the resulting NDVI profile is more or less smooth with all missing values being interpolated. For illustration purposes, the algorithm was introduced with second-order differences in the penalty (Equation (3)). For our research we used third-order differences as in the original work of Whittaker (1923). In this case, the roughness term, \(R\), has to be calculated according to:

\[
R = \sum_i (z_i - 3z_{i-1} + 3z_{i-2} - z_{i-3})^2
\]

(7)

Concerning the smoothing parameter \(\kappa\), it was hypothesized that its value changes only gradually in space. Hence, \(\kappa\) was automatically optimized only for each 5th pixel (in row and column direction) followed by a linear spatial interpolation. This saves computation time as the cross-validated optimization of \(\kappa\) is the most time consuming task within the process. In the progress of Digital Earth, grid computing will in the near future make such simplifications needless (Ehlers 2008). For the present study, \(\kappa\) was varied between \(10^{-1}\) and \(10^1\) on a log \(\kappa\) approximately linear spaced grid (11 values).

The smoother can handle missing values quite easily, even in large stretches. Nevertheless it was decided to filter only those pixels having at least 200 (out of 386) valid measurements. Pixels flagged as missing, cloud, snow, or water were considered as non-valid measurements.

The modified WS was applied to the original SPOT VGT NDVI time series covering South America at 10-day time steps (1998–2008). The processing of the
whole time series (using Matlab 7.5) took 36 hours on an Intel Xeon CPU with two 2.67 GHz processors and 16 GB of RAM.

3.3. Geostatistical assessment of image quality

A geostatistical analysis was performed to assess the SNR of the data before and after filter application (Chappell et al. 2001, Asmat et al. 2007, Atkinson et al. 2007a, 2007b). On the one hand this permits quantifying the performance of the filtering attempt in a scientific perspective. At the same time the SNR can be considered an important quality indicator to be associated (as metadata) with any E.O. data set of the Digital Earth data repository.

For application of the WS, the SPOT imagery was divided into blocks of 200 × 200 pixels. To extract the data required for the geostatistical analysis, the blocks were further subdivided into 3 × 3 non-overlapping cells (each with 66 × 66 km²). Variogram fitting was done in each cell and for each date independently. The sole condition for variogram modeling was that (in the cell being processed) more than half of the pixels were valid. If this was not the case, the cell was flagged as un-processed.

To avoid unreliable variogram values at a large distance \( x \), variogram values were computed up to the maximum distance \( d_{\text{max}} = 44 \) km, equal to two-thirds the extent of the image cells (Garrigues et al. 2006). Similar to the approach proposed by Garrigues et al. (2006), a weighted sum of two elementary functions (spherical and exponential) was used to model the variogram. In this way it was possible to account for multi-scale spatial structuring of the scenes.

The spherical model is defined as follows

\[
\gamma_1 = c_0 + c \left( \frac{3x}{2r_1} - 0.5 \left( \frac{x}{r_1} \right)^3 \right) \quad \text{for} \quad x \leq r_1
\]

\[
\gamma_1 = c_0 + c \quad \text{for} \quad x > r_1
\]

with \( c_0 \), nugget variance; \( c \), structured sill; and \( r_1 \), range of the spherical model. 

The exponential model is

\[
\gamma_2 = c_0 + c \left( 1 - \exp \left( -\frac{3x}{r_2} \right) \right)
\]

with \( r_2 \), range of the exponential model 

Both functions were nested together to yield the final model

\[
\gamma = (b \cdot \gamma_1 + (1 - b) \cdot \gamma_2)
\]

where \( b \) is the regionalization factor; fraction attributed to the spherical model (\( 0 \leq b \leq 1 \)).

The mean length scale (\( D_c \)) of the nested variogram is given by the following expression (Garrigues et al. 2006)

\[
D_c = \sqrt{\frac{b \cdot 2\pi^2}{9} + (1 - b) \cdot \frac{\pi^2}{5}}
\]
To fit this multi-scale variogram to experimental data, five parameters needed to be estimated: \( c_0 \), \( c \), \( b \), \( r_1 \) and \( r_2 \). Since this optimization had to be performed for more than 1 Mio. cells (66 \( \times \) 60 [cells] \( \times \) 386 [layer]), the parameters could not be estimated through numerical optimization. Instead, a much faster look-up-table approach (LUT) was preferred.

The LUT-related parameter ranges and the number of corresponding elements are specified in Table 2. A total number of 612,375 different combinations of the five variogram parameters were evaluated within the LUT. For each parameter combination the theoretical variograms for 35 lag distances, \( x \) between 1 and 44 km were calculated and stored. A few example variograms are shown in Figure 3c. The spacing of the lag distances was denser at short distances to accentuate the contribution of the small ranges, which are important to correctly estimate the nugget variance, \( c_0 \). The precise estimation of the nugget variance is necessary to properly assess the SNR of the image cell (Asmat et al. 2007, Atkinson et al. 2007a, 2007b)

\[
\text{SNR} = \frac{\mu}{\sqrt{c_0}}
\]  

with \( \mu \), average NDVI value within the image cell.

In the LUT, the nugget variance, \( c_0 \) was nested to the linearly spaced structured sill, \( c \) via a factor \( f \); see text in Table 2). In this way a denser sampling for small \( c_0 \) was achieved (Figure 3a). For the regionalization factor \( b \), seven levels were used (Table 2). For each \( b \) between 40 and 56 combinations of \( r_1 \) and \( r_2 \) were employed. The resulting distribution of \( Dc \) is shown in Figure 3b. Note that the settings were optimized by trial and error to restrict the size of the LUT while sampling well different curve forms.

Table 2. Specification of the parameter settings for establishing the theoretical variograms in the LUT used for fitting the experimental data.

<table>
<thead>
<tr>
<th>Variable</th>
<th>min/max</th>
<th>Distribution ['number of levels']</th>
</tr>
</thead>
<tbody>
<tr>
<td>Lag distances (km)</td>
<td>( x )</td>
<td>1.4–44, 1.4, 2, 2.2, 2.8, 3, 3.2, 3.6, 4:1:22, 24:2:32, 35:3:44 [35]</td>
</tr>
<tr>
<td>Structured sill</td>
<td>( c )</td>
<td>10–710, Equally spaced values [71]</td>
</tr>
<tr>
<td>Nugget variance</td>
<td>( c_0 )</td>
<td>0.1–355, *Nested with ( c ) [25]</td>
</tr>
<tr>
<td>Regionalization factor</td>
<td>( b )</td>
<td>0–1, *Equally spaced values [7]</td>
</tr>
<tr>
<td>Range of exponential model (km)</td>
<td>( r_1 )</td>
<td>2–44, [na] [4] [7] [7] [8] [13] [40]</td>
</tr>
<tr>
<td>Range of spherical model (km)</td>
<td>( r_2 )</td>
<td>2–44, [40] [13] [8] [7] [7] [4] [na]</td>
</tr>
<tr>
<td>Effective scale length (km)</td>
<td>( Dc )</td>
<td>2–37, [40] [52] [56] [49] [56] [52] [40]</td>
</tr>
</tbody>
</table>

*aThe nugget variance \( c_0 \) was nested with the structured sill, \( c \) by: \( c_0 = c/f \) with \( f \) taking 25 equally spaced values from 2 to 150.

*bThe regionalization factor \( b \) was linked to the ranges \( (r_1 \) and \( r_2 \) of the exponential and spherical models. The table gives in brackets the number of range levels (between 2 and 44 km) for each value of the regionalization factor, \( b \). Together, the three parameters \( (r_1, r_2, \) and \( b \) define the effective scale length, \( Dc \) (see Equation 12) and the number of \( Dc \) levels within each class of \( b \) (last line).
To fit the experimental variograms, the semivariances were extracted for each image cell and the 35 lag distances, $x$, indicated in Table 2. The LUT entry yielding the lowest RMSE between the theoretical and the experimental variogram was taken as the optimum solution. The corresponding parameter values were stored for later analysis together with the RMSE of the best fit. If no appropriate fit could be achieved (RMSE $>50$; with $0 \leq \text{NDVI} \leq 250$), the cell was flagged. This happened occasionally, for example because of non-stationarity in the data, or as a consequence of very poor data quality. The final analysis regarding the image quality was based on those cells where at least 63% (243 out of 386) of the variograms were fitted with sufficiently high accuracy.

4. Characteristics of the filtered time series

Guo et al. (2010) pointed out that Digital Earth, as an approach to exploring global issues and the Earth system, should be further enhanced by ‘...giving priority to solving some of the [major] challenges facing human society such as natural resource depletion...environmental degradation...and, in particular, global climate change.’ The mentioned issues can be in principle well addressed by remotely sensed time series. This will be illustrated in the following subsections. The chosen examples demonstrate the quality of the filtered time series (mainly through comparison with the original data set). Without substantial improvements in data quality it is probably not possible to address natural resource depletion, environmental degradation or global climate change through satellite observations.

4.1. NDVI profiles of temporally invariant targets

Within Digital Earth, any satellite-based land surface monitoring program will require that the recorded signal is related as much as possible to the state of the surface, while being minimally affected by perturbing factors such as the state of the atmosphere, the measurement geometry, or sensor noise. MVC can only partly achieve this goal as demonstrated by a recorded time series over a pseudo-invariant
target (Figure 4a). For the illustration, a pixel situated within the evergreen Atlantic forests of Brazil was selected, a biodiversity hot spot area (Myers et al. 2000). The climate in this region shows only relatively small year-to-year variations (Rao and Hada 1990). The intra-year LAI dynamics of these forests is known to be low. The profiles derived from the original data reveal unrealistic scattering with sudden strong drops in NDVI. Such strong NDVI oscillations over an evergreen forest are not compatible with the gradual process of vegetation change. They must therefore be regarded as noise and be removed (Chen et al. 2004). If such noise is not removed prior to data interpretation, a monitoring application within Digital Earth would incorrectly indicate a strong environmental degradation. Application of the WS led to smooth NDVI profiles (Figure 4b). The filtered curves fall within a small NDVI range as expected for such a target. A change detection algorithm would not give a false alarm.

4.2. Signal-to-noise ratio (SNR)

Compared to the input data, the smoothed data set shows a significant increase of the geostatistically estimated SNR (Figure 5b). On average, the increase in the SNR amounts to 33 units (median: 23 units). At the same time the coefficient of variation decreased indicating a spatially more homogeneous data quality (not shown). Apart from the Andes Mountains in the central western part of the frame where average annual NDVI is below 0.3 (Figure 1c), the geostatistical analysis indicated for most part of the area an SNR of at least 50–100 (Figure 5a). SNR in this range are mandatory for many coarse scale remote sensing applications (Atkinson et al. 2005). As the image-derived SNR clearly indicates the usefulness of E.O. data for
monitoring purposes, it is recommended to include this kind of information in metadata descriptors.

4.3. Temporal persistency of z-score values

Most existing agricultural and drought monitoring programs (e.g. USDA, JRC-MARS) rely in some way on satellite-derived maps of vegetation anomalies (Ji and Peters 2003, Zhang et al. 2005). Likewise, any global change research within the frame of Digital Earth (Shupeng and van Genderen 2008) will probably also have to build on anomaly detection. Anomaly maps compare the actual situation with the long-term average. If these maps are to be useful, false alarms should be avoided and spatial patterns should be consistent.

To illustrate the problem, Figure 6 shows a z-score profile for a randomly chosen grassland pixel. The z-score indicates how many standard deviations an observation ($x$) is above or below the mean. It is a dimensionless quantity derived by subtracting the population mean ($\mu$) from an individual raw score and then dividing the difference by the standard deviation ($\sigma$) of the population:

$$z = \frac{x - \mu}{\sigma}$$

The temporal profile derived from the filtered data (bold line) shows a clear pattern with a significant negative vegetation anomaly ($z < -1$) from July 2003 to May 2004 and two periods of positive anomalies at the beginning of 2003 and in the second half of 2005. The z-score profile derived from the original data (dashed line) broadly follows the same pattern, but with (too) many short-term fluctuations. The temporal
persistency of the original data is generally low. Occasionally, a strong positive vegetation anomaly \((z > 1)\), followed by a negative anomaly \((z < -1)\), can be observed within only one time step (e.g. 10 days). Such an implausible behavior is for example present around April 2003, and most probably does not correspond to a real drop in vegetation activity. Another strange oscillation can be seen at the beginning of 2006. In the case of the filtered data, the noise is effectively reduced resulting in curves with a much higher temporal persistency. If unfiltered data sets would be uploaded in the Digital Earth database, inexperienced analysts would misinterpret the observed anomalies. This should be avoided if the concept of Digital Earth is to be widely adopted.

This statement is further confirmed by the findings summarized in Figure 7. Interestingly, before filter application (Figure 7a), the overwhelming majority (>95%) of all vegetation anomalies, positive as well as negative, lasted only one dekad (10 days), a period too short to be attributable to a meso-scale meteorological forcing. At the same time, the typical duration of ‘normal’ vegetation conditions \((-1 \leq z \leq 1)\) was also very short (2–4 dekads). This confirms the basic hypothesis of this study that large parts of the observed NDVI variations are due to atmospheric noise and undetected clouds rather than changes in the land surface conditions. In an agricultural or drought monitoring program within Digital Earth, such unfiltered data would inevitably lead to too many false alarms.

After smoothing, the typical length of positive and negative vegetation anomalies rises to 3–7 dekads (Figure 7b) with ‘normal’ vegetation conditions typically holding between 5 and 11 dekads. Such a distribution looks more plausible for an assumed meteorological forcing.
4.4. Distinction of plant functional types

Time series of vegetation indices constitute a valuable data source for deriving continental-scale land cover maps and plant functional types (Paruelo et al. 2001). The distinction of plant functional types is often hampered by poor data quality (Xiao et al. 2002). Exemplarily, this can be appreciated from Figure 8a showing NDVI profiles of five near-by pixels belonging to different (GLC2000) land cover classes. After application of the WS (Figure 8b) the curves approach the upper envelope of the original data. Spurious NDVI drops are removed resulting in smooth profiles. The different surfaces can be well discerned in terms of their average, as well as minimum and maximum vegetation density, the phasing of vegetation onset, peak time and senescence, the number of growth cycles, as well as the rates of leaf growth and senescence. The same information could in principle be derived from the unfiltered data set. However, the phasing would be less evident and a given NDVI minimum could be solely an artifact resulting, for example, from an undetected cloud.

To assess if the noise removal would (positively) affect the classification accuracy of a land cover map, a small test area (400 × 400 km²) in Minas Gerais, Brazil was selected. For the test area we assumed that the GLC2000 land cover map is accurate. The inter-class distances (and hence the class separabilities) were calculated between five plant functional types (same as in Figure 8) from 36 NDVI values in 2005/2006 (Table 3). The table reports the class-by-class Jeffries–Matusita (JM) distances for the filtered data set in absolute units and relative to those obtained without filtering.

The JM distance between a pair of probability functions is a measure of the average distance between the two class density functions (Schmidt and Skidmore 2003). The JM distance is asymptotic to the value 2 for increasing class separability.
A distance of 2.0 between two classes would imply classification of those two classes with 100% accuracy. In the above example, the JM distances were usually around 1.3 indicating a good (but not perfect) separability of the various classes. Only the separability of shrub and herbaceous covers was difficult, indicated by the JM distance of about 0.9. In all cases, the filtered data gave higher JM values as compared to the unfiltered data (Table 3). The relative increase from unfiltered to filtered data varies from case to case but was >10% for several cases. This can be considered a clear indication for an improved quality of the filtered data set. Similar

Table 3. Jeffries–Matusita distances between five broad land cover classes after application of the Whittaker smoother (in bold). In parentheses the relative increase/decrease with respect to the original data. The JM distances were calculated from 36 (normalized) decadal values (July 2005–June 2006). The pixels belonging to the five classes have been extracted using the GLC2000 land cover map. The analyzed data set covers a small area in Minas Gerais, Brazil (400 × 400 km).

<table>
<thead>
<tr>
<th>Class</th>
<th>Deciduous forest</th>
<th>Shrub cover</th>
<th>Herbaceous cover</th>
<th>Crop land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evergreen forest</td>
<td>1.22 (4.6%)</td>
<td>1.32 (0.7%)</td>
<td>1.32 (1.3%)</td>
<td>1.38 (4.0%)</td>
</tr>
<tr>
<td>Deciduous forest</td>
<td>1.28 (9.5%)</td>
<td>1.29 (10.8%)</td>
<td>1.20 (9.7%)</td>
<td></td>
</tr>
<tr>
<td>Shrub cover</td>
<td></td>
<td>0.94 (17.6%)</td>
<td></td>
<td>1.38 (13.5%)</td>
</tr>
<tr>
<td>Herbaceous cover</td>
<td></td>
<td></td>
<td></td>
<td>1.36 (17.2%)</td>
</tr>
</tbody>
</table>
findings were reported in the literature. For example Xiao et al. (2002) stressed the importance of a proper cloud removal and atmospheric correction for optimum land use and land cover classification.

4.5. Phasing of key phenological events

Continental data sets reporting the intra-annual NDVI dynamics and phasing of key vegetation developmental stages are required in numerous applications ranging from wildlife distribution modeling (Pettorelli et al. 2005) to biodiversity mapping (Coops et al. 2009). Phenological observations also constitute a main pillar for global change assessments (White et al. 1997), because the development of plants reflects well the (bio)climatic conditions of the habitat. In several countries (e.g., Germany), long ground observation records exist (> 100 yr), that allow to compare the current situation with the previous conditions. However, these observations are only point measurements and cannot easily be spatialized. From E.O. on the other hand, one can get a complete spatial coverage, which however does not reach far enough back in time. Thus space and field observations can complement each other in the Digital Earth approach. This, however, requires that the phenological information can be derived with sufficiently high accuracy from the satellite observations.

From Figure 9 it can be seen that important phenological indicators can be readily derived from the filtered data set because most of the artifacts that usually hamper data analysis were removed. The two maps on the top (Figure 9a and 9b) depict the timing of the vegetation onset at the end of the dry season, and the time of maximum greenness. The map in Figure 9c shows the intra-annual NDVI amplitude. These three metrics were derived for each individual year and averaged across 1998–2008 for plotting purposes. The time of minimum, respectively, maximum NDVI was found through simple search functions looking at the individual years of the smoothed data sets. The intra-annual NDVI amplitude corresponds to the difference between the maximum and minimum NDVI associated with the two time stamps.

The different indicators in Figure 9 broadly reflect the major biomes (Figure 1a) and land cover classes found in the study region (Figure 1b). The (evergreen) tropical moist forests generally have a low dynamic range (Figure 9c) with a high average NDVI. The minimum NDVI occurs generally during austral summer (November–March) whereas the NDVI peak is usually between July and October (Figure 9a and 9b). Deciduous forests have a lower average NDVI compared to the evergreen forests with a higher dynamic range. Their marked minimum falls in the dry period around September/October during the leaf-off period. A large NDVI amplitude is also characteristic of xeric shrublands and cropland in the biomes of tropical/subtropical shrublands and temperate grasslands. The minimum NDVI of these classes occurs between August and October while the peak time is in summer (January–March). Bare areas in the montane shrubland biome are characterized by a low average NDVI and almost flat NDVI curves.

As expected for the large area covered by the data set, the key phenological events exhibit a clear latitudinal dependence, following the prevailing precipitation and temperature patterns (Figure 9d). The observed gradient between 10° and 30° S reflects shifts in growing seasons that are further modulated by the actual land cover.
For example, the time of maximum vegetation density is generally shifted to earlier dates moving southwards. At 25° S, the deciduous forests reach the peak NDVI almost 1 month earlier than the grasslands, whereas almost no differences can be observed at 20° S (Figure 9d).

5. Conclusions
The paper presented a high quality coarse resolution data set of vegetation activity covering large parts of South America. The time series is potentially useful for
environmental and vegetation related studies within Digital Earth. It can be provided free of charge for non-commercial users to foster remote sensing applications within the environmental sciences and to stimulate comparison with other existing data sets and algorithms.

For the filtering of the input data the study relied on the WS. The WS was selected amongst other candidates because it balances in a simple and straight-forward way the fidelity to the observations with the roughness of the smoothed curve. The smoothness of the curve is controlled by a single parameter, which is determined from the data itself. Moreover, this algorithm is extremely fast and interpolates automatically, while user intervention is minimal. It has no edge effects and does not assume periodicity of the data. The algorithm can be implemented very quickly in high-level computing languages such as Matlab, and is available free of charge via the Internet at http://pubs.acs.org. Together this makes the smoother an appealing candidate for filtering other E.O. time series to be included in Digital Earth.

The study also presented several examples demonstrating the quality of the processed data as compared to the original MVC-NDVI input. Quality indicators derived in this way should be published as metadata when uploading E.O. time series in the Digital Earth repository. These indicators should have a close relation with the usefulness of the imagery for studying environmental problems. Without providing quality indicators, the risk would be too high that (inexperienced) users misinterpret the data.

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Paul Eilers was trained as an electronic engineer, but he gradually moved into statistics. He applied it in a variety of fields: biology, environmental research and management, medical research, and the social sciences. He has a special interest in smoothing methods, complex statistical models and scientific computation. He has published nearly 100 methodological and applied papers covering a diverse array of subjects. Presently he is a Professor of Genetical Statistics in the Biostatistics Department of the Erasmus Medical Center in Rotterdam, The Netherlands.
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