International Journal of Remote Sensing

ISSN: 0143-1161 (Print) 1366-5901 (Online) Journal homepage: http://www.tandfonline.com/loi/tres20

Assessing the performance of smoothing functions to estimate land surface phenology on temperate grassland

Bruno Lara & Marcelo Gandini

To cite this article: Bruno Lara & Marcelo Gandini (2016) Assessing the performance of smoothing functions to estimate land surface phenology on temperate grassland, International Journal of Remote Sensing, 37:8, 1801-1813, DOI: 10.1080/2150704X.2016.1168945

To link to this article: http://dx.doi.org/10.1080/2150704X.2016.1168945

Published online: 11 Apr 2016.

INTERNATIONAL JOURNAL OF REMOTE SENSING, 2016
VOL. 37, NO. 8, 1801–1813
http://dx.doi.org/10.1080/2150704X.2016.1168945

Taylor & Francis
Taylor & Francis Group

Assessing the performance of smoothing functions to estimate land surface phenology on temperate grassland

Bruno Lara[a,b] and Marcelo Gandini[a]

[a]Laboratorio de Investigación y Servicios en Teledetección de Azul, Facultad de Agronomía, Universidad Nacional del Centro de la Provincia de Buenos Aires (LISTA-FAA-UNCPBA), Azul, Argentina; [b]Comisión de Investigaciones Científicas (CIC) de la Provincia de Buenos Aires, La Plata, Argentina

ABSTRACT
NDVI (Normalized Difference Vegetation Index) time-series have been used for permitting a land surface phenology retrieval but these time series are affected by clouds and aerosols, which add noise to the signal sensor. In this sense, several smoothing functions are used to remove noise introduced by undetected clouds and poor atmospheric conditions, but a comparison between methods is still necessary due to disagreements about its performance in the literature. The application of a smoothing function is a necessarily previous step to describe land surface phenology in different ecosystems. The aims of this research were to evaluate the consistency of different smoothing functions from TIMESAT software and their impacts on phenological attributes of temperate grassland – a complex mosaic of land uses with natural vegetated and agricultural regions using NDVI-MODIS time series. An adaptive Savitzky–Golay (SG) filter, Asymmetric Gaussian (AG) and Double Logistic (DL) functions to fitting NDVI data were used and their performances were assessed using the measures root mean square error (RMSE), Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and bias. Besides, differences on the estimation of the start of the growing season (SOS) and the length of the growing season (LOS) were obtained. High and low RMSE over croplands and grassland were observed for the three smoothing functions; in the rest of the region, the SG filter showed more reliable results. Patterns of difference on the estimation of SOS and LOS between SG filter and the other two models were randomly distributed, where differences of 20–50 days were found. This study demonstrated that methods from TIMESAT software are robust and spatially consistent but must be carefully used.

ARTICLE HISTORY
Received 17 September 2015
Accepted 11 March 2016

1. Introduction

Land surface phenology responds to climatic drivers and it is key to many earth surface processes. Remote-sensing methods have been used to study the dynamic and spatial distribution of vegetation cover at different spatial and temporal scales. In this respect, NDVI (Normalized Difference Vegetation Index) is one of the most commonly used indices because

CONTACT Bruno Lara brunolara73@gmail.com Laboratorio de Investigación y Servicios en Teledetección de Azul, Facultad de Agronomía, Universidad Nacional del Centro de la Provincia de Buenos Aires (LISTA-FAA-UNCPBA), Azul, Buenos Aires, Argentina

it is a linear estimator of the fraction of photosynthetically active radiation intercepted by vegetation (fAPAR) (Wang et al. 2004). Radiation interception is the main process controlling carbon gains (Monteith 1981) and, hence, NDVI has been used to describe and to analyse regional and local patterns of net primary productivity (NPP) (Paruelo et al. 1997; Paruelo, Jobbágy, and Sala 2001; Alcaraz-Segura et al. 2009).

NDVI time-series have been widely used to identify ecosystem functional types (Paruelo, Jobbágy, and Sala 2001; Ivits et al. 2013; Atzberger and Eilers 2011), in the mapping landscape heterogeneity (Ali et al. 2014; Barraza et al. 2013; Li et al. 2012), to evaluate the relationship between NDVI (or derived metrics of land surface phenology) and climatic drivers (Yang et al. 2012; Melendez-Pastor et al. 2010; van Leeuwen et al. 2013), to predict yield in agriculture (Atzberger 2013; Rembold et al. 2013; Holzman, Rivas, and Piccolo 2014), to monitor drought (Tucker and Choudhury 1987; Kogan 1997) and in the use of vegetation anomalies for index-based insurances (de Leeuw et al. 2014). The use of NDVI time-series allows obtaining different aspects of the exchange of matter and energy between the biota and the atmosphere, i.e. ecosystems functional attributes (Pettorelli et al. 2005). These ecosystems functional attributes have some advantages over the traditional use of structural variables: variables describing ecosystem functioning have a faster response to disturbances because structural inertia might delay the perception of disturbances, and besides functional attributes allow the qualitative and quantitative characterization of ecosystems services (e.g. water cycling, carbon sequestration) (Alcaraz-Segura et al. 2009).

The applications mentioned rely on the reliability and consistency of the analysed time series. The direct extraction of phenological metrics is difficult because satellite data are noisy due to atmospheric effects, bidirectional effects, snow/cloud cover and variations in viewing and illumination geometry. The Constrained View angle–Maximum Value Composite (CV–MVC) and Maximum Value Composite (MVC) techniques allow reduction of a considerable amount of noise that is present in different images (Solano et al. 2010) but do not result in noise-free products. To overcome the problems associated with remaining noise, various methods have been developed to estimate phenology and production metrics based on NDVI time-series. Some of them are: principal component analysis (Eastman 2009), Fourier or harmonic analysis (Jakubauskas, Legates, and Kastens 2001; Moody and Johnson 2001; Leinenkugel et al. 2013), wavelet decomposition (Yang et al. 2012), the Whitakker smoother (Atzberger and Eilers 2011), double logistic (DL) function (Beck et al. 2006; Liu et al. 2013), the asymmetric Gaussian (AG) function fitting (Jönsson and Eklundh 2002), Savitzky–Golay (SG) filters (Jönsson and Eklundh 2004; Tan et al. 2011), the polynomial splines (Eilers 2003). The determination of the start of the growing season (SOS) and other phenological attributes over the time series is often very complex. In this sense, there is currently no agreement within the scientific community regarding the optimum way of extracting land surface phenology; an intercomparison and interpretation of many approaches are discussed by White et al. (2009).

Beck et al. (2006) found that the DL function describes NDVI data better than the AG function over high-latitudes environments, as suggested by root mean square error (RMSE). However, Zhu and Meng (2015) found that the performance of the AG function in reducing noise of the NDVI time series is better than the DL function over grasslands of semi-arid areas. Hird and McDermid (2009) demonstrated the general superiority of AG and DL functions by comparing to the other alternative filters (including SG filter). AG and DL functions showed a balanced ability to reduce noise while maintaining the NDVI time series integrity. Atkinson et al. (2012) analysed four smoothing functions (AG, DL, Fourier and

Whittaker approaches) and they found that only the Fourier and Whittaker approaches produced smaller RMSE values over the agricultural as well as natural vegetated regions. The variety of results and the lack of consensus about those methods need further discussion. There is insufficient information in the literature to conclude on these issues, and there are no comparisons in the Southern temperate grasslands.

According to the above mentioned, an assessment of the quality of smoothing functions should be made over each ecosystem. In this sense, the aims of this article were to evaluate and to analyse the consistency of different smoothing functions that are available in TIMESAT software (Jönsson and Eklundh 2004) and their impacts on the estimation of phenological attributes (SOS and length of the growing season – LOS-) on temperate grassland of Buenos Aires province, Argentina. This region is an ideal location due to the high heterogeneity of landscapes and for being one the most productive areas in the country (Matteucci 2012; Lara and Gandini 2014). The main advantages of TIMESAT program are that the software is both friendly to use and freely available.

2. Materials and methods

2.1. *Study area*

Pampa Ecoregion (Figure 1) supports one of the largest temperate grasslands on the globe and has undergone major changes since the sixteenth century (Vega et al. 2009; Matteucci 2012). This ecoregion has natural subunits where a mosaic of land uses is superimposed. This mosaic has changed over time increasing at a fast rate in the last two decades (Viglizzo et al. 2001; Baldi, Guerschman, and Paruelo 2006; Lara and Gandini 2014). The variety of land cover, natural or semi-natural grassland (*Paspalum* sp., *Stipa* sp., *Melica* sp., *Phyla* sp., *Cirsium* sp., *Cypella* sp.), sown pastures (*Festuca* sp., *Agropyron* sp.), annual crops (wheat, oats, corn, soybean, sunflower) provide an appropriate location that allows for the analysis of land surface phenology in different ecosystems with a very different behaviour.

2.2. *Data*

We used the MOD13Q1 16-days 250 m NDVI products from Terra's Moderate Resolution Imaging Spectroradiometer (MODIS). The imagery covered a one-year time series, from

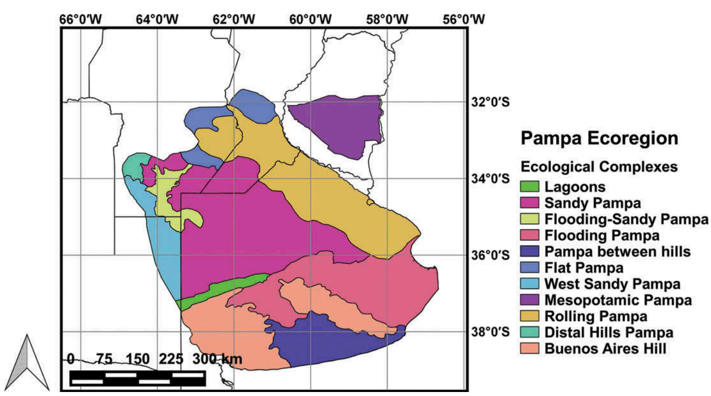

Figure 1. Pampa ecoregion and ecological complexes by Matteucci (2012).

July 2001 to June 2002; the scene used was h13v12. Considering that El Niño Southern Oscillation (ENSO) has a high impact on the ecosystem response (van Leeuwen et al. 2013; Broich et al. 2014), we previously evaluated that growing season was characterized by an ENSO-phase 'neutral' (Wolter and Timlin 2011) resulting 2001–2002 season.

2.3. *Smoothing*

TIMESAT program implements three processing methods based on least-squares fits to the upper envelope of the vegetation index data (Eklundh and Jönsson 2009). An adaptive SG filter (Equation (1)) uses local polynomial functions in the fitting.

$$\sum_{j=-n}^{n} c_j y_{i+j}, \tag{1}$$

where the weights are c_j and each data value $y_{i,} i = 1, 2, \ldots, N$ is replaced by a linear combination of nearby values in a window (n, defined by the user); these windows are overlapping. For each data value the following quadratic polynomial,

$$f(t) = c_1 + c_2 t + c_3 t^2, \tag{2}$$

is fitted to all $2n + 1$ points in the moving window and the value y_i is replaced with the value of the polynomial at position t_i, where t indicates the time. In our case, we used a window with $n = 3$.

The other two methods are AG (Equation (3)) and DL functions (Equation (4)), where data are fitted to non-linear model functions. The basis function of AG is the following:

$$g(t; x_1, x_2, \ldots, x_5) = \begin{cases} \exp\left[-\left(\frac{t-x_1}{x_2}\right)^{x_3}\right] & \text{if } t > x_1 \\ \exp\left[-\left(\frac{x_1-t}{x_4}\right)^{x_5}\right] & \text{if } t < x_1, \end{cases} \tag{3}$$

where x_1 determines the position of the maximum or minimum with respect to the independent time variable t. x_2 and x_3 determine the width and flatness (kurtosis) of the right function half. Similarly, x_4 and x_5 determine the width and flatness of the left half.

On the other hand, the basis function of the smoothing DL is the following formula,

$$g(t; x_1, \ldots, x_4) = \frac{1}{1 + \exp\left(\frac{x_1-t}{x_2}\right)} - \frac{1}{1 + \exp\left(\frac{x_3-t}{x_4}\right)}, \tag{4}$$

where x_1 determines the position of the left inflection point while x_2 gives the rate of change. In the same way, x_3 determines the position of the right inflection point while x_4 gives the rate of change at this point.

The pixel reliability band (MOD13Q1) was used to weight each pixel in the time series: value 0 (good data) had full weight (1.0), values 1–2 (marginal data, snow/ice) had half weight (0.5) and value 3 (cloudy) had low weight (0.1). This procedure was applied to the three smoothing functions. For SG filter we did not fit the upper envelope, whereas for AG and DL functions one additional fit was applied where the weights of the values below the fitted curve is decreased forcing the fitted function towards the upper envelope.

More details of the algorithms can be found in the work by Jönsson and Eklundh (2002), Beck et al. (2006) and Chen et al. (2004).

2.4. *Assessment of the smoothing functions*

The performance of the smoothing functions was assessed using four statistical measures: RMSE, Bias, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), pixel to pixel,

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (\mathrm{NDVI_{obs}} - \mathrm{NDVI_{fit}})^2}{N}}, \tag{5}$$

$$\mathrm{Bias} = \frac{\sum_{i=1}^{N} (\mathrm{NDVI_{obs}} - \mathrm{NDVI_{fit}})}{N}, \tag{6}$$

where N is the number of images, $\mathrm{NDVI_{obs}}$ and $\mathrm{NDVI_{fit}}$ are the observed and fitted NDVI values, respectively. Negative values of bias indicate an overestimation and positive values indicate an underestimation. Assuming that the noise in the NDVI imagery is negatively biased, negative values of bias (overestimation) offer the spatio-temporal patterns of the removed noise (Atzberger and Eilers 2011). Thus, a comparison between bias and cloudiness frequency was analysed.

The AIC was used to measure the model performance by penalizing the number of parameters, whose formula can be written as

$$\mathrm{AIC} = 2k + n[\ln(\mathrm{RSS})], \tag{7}$$

where k is the number of free parameters in the model, n is the number of input data points and RSS is the residual sum of squares between the original data and fitted data. A lower value of AIC would indicate the preferable model. For the AG function, k is equal to 7 ($c_1, c_2, a_1, a_2, a_3, a_4, a_5$), for the DL function, k is equal to 6 ($c_1, c_2, a_1, a_2, a_3, a_4$) and for the SG filter used here, k is equal to 4 (a_0, a_1, a_2 and residuals) (Atkinson et al. 2012; Burnham and Anderson 2002). The BIC, another measure of goodness-of-fit using Bayesian framework, was calculated as

$$\mathrm{BIC} = n \ln\left(\hat{\sigma}^2\right) + k\, ln(n), \tag{8}$$

where $\hat{\sigma}^2$ is the error variance. k and n have a similar meaning to that in the AIC. The BIC penalizes parameter more strongly than does AIC.

2.5. *Extraction of land surface phenology attributes*

The SOS and the LOS were extracted from the three models analysed (AG, DL and SG). A threshold of 20% of the amplitude over the time series to determine the beginning and the end of the growing season was considered. In this case, the minimum NDVI value is given as the average of the left and the right minimum values, and the maximum NDVI value is given by the largest NDVI value on the fitted function during the growing season (Eklundh and Jönsson 2009).

2.6. *Spatial patterns of difference on the estimation of land surface phenology attributes*

The differences on the estimation of SOS and LOS between smoothing functions were obtained by subtracting one map from another, pixel to pixel (i.e. $SOS_{AG} - SOS_{DL}$; $SOS_{SG} - SOS_{DL}$; $SOS_{SG} - SOS_{AG}$, etc.). Thus, the new resultant map shows the spatial patterns of difference (in days) on the estimation of SOS (or LOS).

3. Results and discussion

The performance of models based on NDVI time-series is shown in Figures 2–4. The three smoothing functions presented lower RMSE on the region where grasslands are the dominant land cover (Herrera et al. 2009; Lara and Gandini 2014), and higher RMSE where annual crops represent the most extensive land cover (Baldi, Guerschman, and Paruelo 2006). These results suggest that the exchange between active vegetation cover and bare soil (like in croplands) has certain impact over curve fitting. Similar results were found by Atkinson et al. (2012), where AG and DL functions provided small RMSE values over natural vegetated regions and higher RMSE values over agricultural regions. However, the performance of SG filter has not been assessed by them.

Our results suggest that the adaptive SG filter is more robust than AG and DL functions, possibly due to the lower sensitivity to great variations on NDVI time-series (Eklundh and Jönsson 2009), in disagreement with a previous work by Hird and McDermid (2009). AG and DL functions presented similar results, as expected based on their definition, in agreement with studies carried out on different ecosystems (Beck et al. 2006; Hird and McDermid 2009; Atkinson et al. 2012; Zhu and Meng 2015). The spatial patterns of AIC and BIC values (Figures 3 and 4) are consistent with RMSE values, where, in comparison, the performance of SG function in reducing noise of NDVI time series is better than the performance of AG and DL functions in our study area.

On the other hand, a clear correspondence between cloudiness frequency and the noise removed (negative values of bias) by SG filter was observed (Figure 5). AG and DL functions overestimate NDVI values on regions without presence of clouds. These results demonstrate that SG filter effect and cloudiness frequency are strongly correlated. The

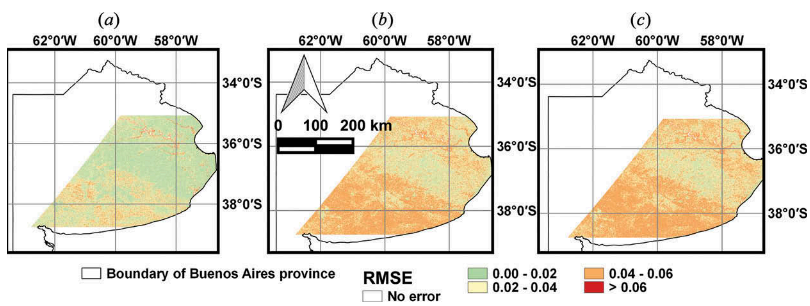

Figure 2. Root mean square error (RMSE) between satellite-observed NDVI and fitted NDVI values using the three smoothing functions from TIMESAT software. (a) Savitzky–Golay filter, (b) Asymmetric Gaussian and (c) Double Logistic functions.

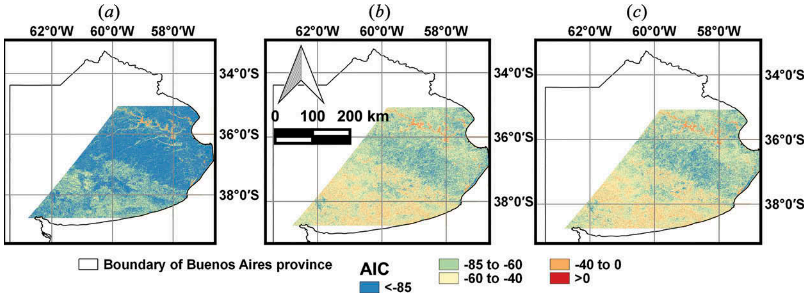

Figure 3. Akaike Information Criterion (AIC) between satellite-observed NDVI and fitted NDVI values using the three smoothing functions. (a) Savitzky–Golay filter, (b) Asymmetric Gaussian and (c) Double Logistic functions.

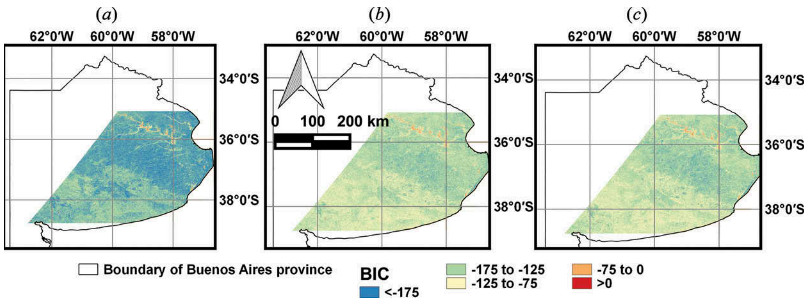

Figure 4. Bayesian Information Criterion (BIC) between satellite-observed NDVI and fitted NDVI values using the three smoothing functions. (a) Savitzky–Golay filter, (b) Asymmetric Gaussian and (c) Double Logistic functions.

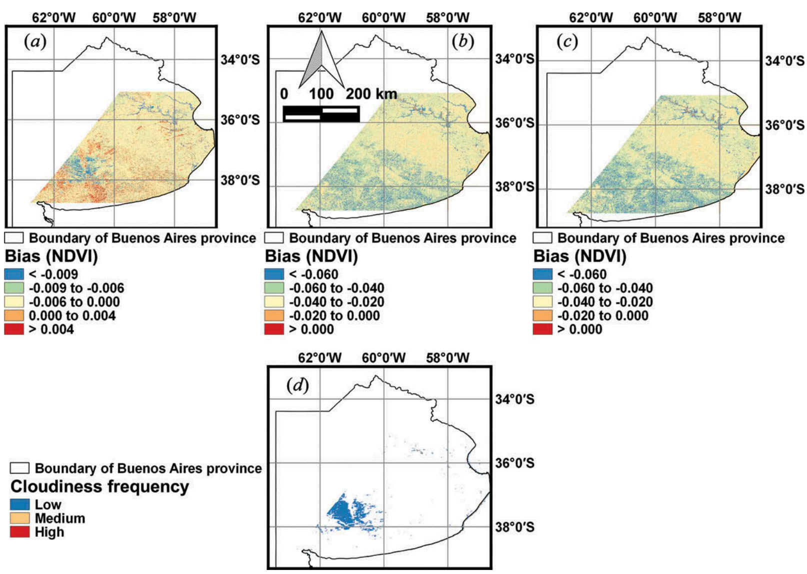

Figure 5. Bias of smoothing functions with respect to satellite-observed NDVI. (a) Savitzky–Golay filter, (b) Asymmetric Gaussian and (c) Double Logistic functions. Negative values of bias indicate an over-estimation (noise removed). (d) Cloudiness frequency of the study area based on MODIS data. Notice how there is a strong correlation between cloudiness frequency and the noise removed by SG filter.

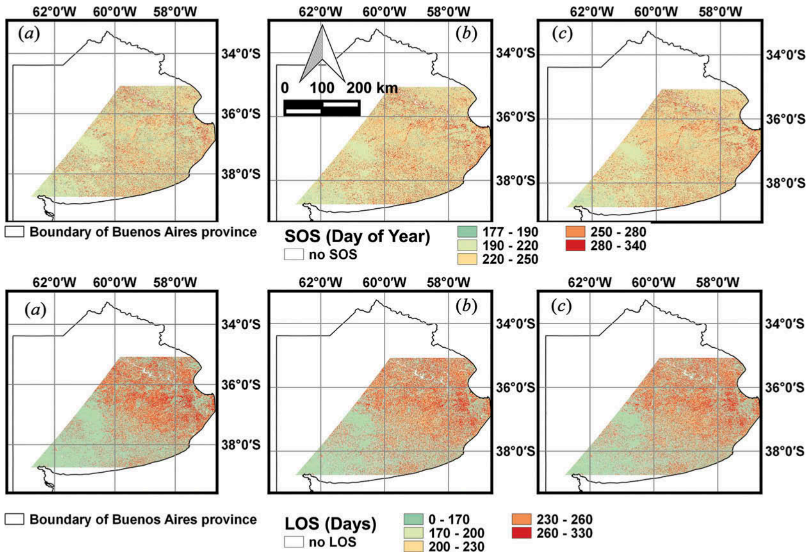

Figure 6. Maps of the start of the growing season (SOS; top) and the length of the growing season (LOS; bottom) of the different methods. (a) Savitzky–Golay filter, (b) Asymmetric Gaussian and (c) Double Logistic.

spatial patterns of the estimated noise by AG and DL functions are random and did not correspond to the cloudiness frequency, which indicate that AG and DL functions overestimate the noise from the NDVI time series.

The maps in Figure 6 show the SOS and the LOS of the different methods for the growing season 2001–2002. Patterns of difference on the estimation of SOS between DL and AG models did not show a definite spatial pattern, but was randomly distributed in the study area and the values of difference are low (in days) (Figure 7). These results indicate that both AG and DL approaches in the TIMESAT software produce similar results when the time-series data is complete. Similar results were obtained by Gao et al. (2008). Although patterns of difference on the estimation of SOS between SG filter and the other two functions (DL and AG models) show a random distribution (without a definite spatial pattern), differences mainly up to 30 days were found over the entire study area (Figure 7). These results suggest that both AG and DL models show a delay on the estimation of SOS with respect to SG.

In the same way that patterns of difference on the estimation of SOS, major differences to estimate LOS between AG and DL models were not found (Figure 8). Although a strong spatial pattern is not observed, the adaptive SG filter tends to overestimate and underestimate LOS with respect to AG and DL models (mainly between 20 and 50 days) (Figure 8). The obtained results suggest that the three processing methods from TIMESAT software (Jönsson and Eklundh 2004) are spatially consistent to estimate phenological attributes such as the SOS and the LOS but there are differences in results that may be important depending on the accuracy required (De Castro et al. 2014; Jin and Eklundh 2014; Hmimina et al. 2013). While a definite spatial pattern of differences (between models) on the estimation of the descriptors of ecosystem functioning analysed in this paper was not found, the adaptive SG filter showed a better performance than the other smoothing functions (DL and AG), which were evaluated using RMSE, AIC and BIC statistics, pixel to pixel. This could strongly impact on other important

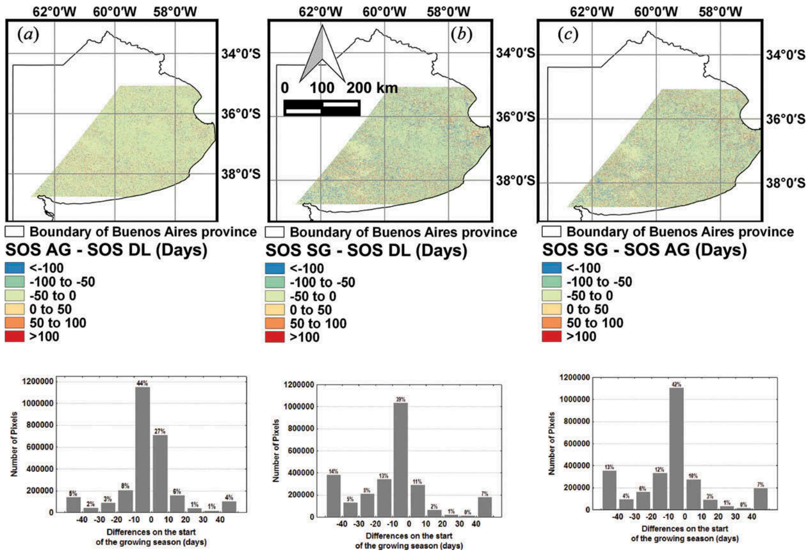

Figure 7. Spatial patterns of the differences (in days) on the estimation of start of the growing season (SOS) between smoothing functions. (a) Asymmetric Gaussian function (AG) minus Double Logistic function (DL). (b) Savitzky–Golay filter (SG) minus Double Logistic function (DL). (c) Savitzky–Golay filter (SG) minus Asymmetric Gaussian function (AG). Frequency distribution, scaled between −50 and 50 days, of the differences on the SOS for the study area are shown below.

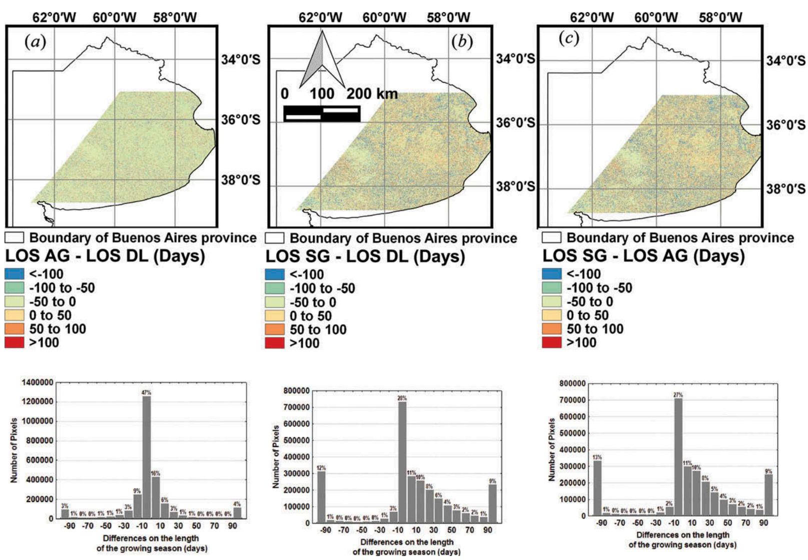

Figure 8. Spatial patterns of the differences (in days) on the estimation of the length of the growing season (LOS) between smoothing functions. (a) Asymmetric Gaussian function (AG) minus Double Logistic function (DL). (b) Savitzky–Golay filter (SG) minus Double Logistic function (DL). (c) Savitzky–Golay filter (SG) minus Asymmetric Gaussian function (AG). Frequency distribution, scaled between −100 and 100 days, of the differences on the LOS for the study area are shown below.

attributes not evaluated here: annual integral of NDVI, dates of maximum and minimum NDVI, maximum NDVI and annual relative range.

The current work provides valuable information about the implementation of fitting techniques, and associated errors in the extraction of phenological attributes. This information should be of value for various studies that attempt to characterize land surface phenology like an input to modelling carbon dynamics or complex climatic models considering the lack of accurate ground observations of phenological events at regional scale.

4. Conclusion

The methodology used allowed us to evaluate and to analyse the performance of different smoothing functions of TIMESAT software and their impact on SOS and LOS (descriptors of ecosystem functioning) on a complex and heterogeneous landscape like the temperate grassland of Buenos Aires province (Argentina). The three analysed models (AG and DL functions, SG filter) showed variations with respect to the observed NDVI values, mainly where annual crops represent the most extensive land cover. Over the entire study area, SG filter showed a better performance than AG and DL functions, which were evaluated by using RMSE, AIC, BIC and BIAS statistics. Only SG filter showed a balanced ability to reduce noise while maintaining the relevant NDVI signal integrity, where a strong correlation between the noise removed and cloudiness frequency was observed.

We found differences of 20 up to 50 days between SG filter and the other two models on the estimation of SOS and LOS but a spatial pattern was not found. This suggests that the three processing methods from TIMESAT software are spatially consistent to estimate phenological attributes. However, we found that both AG and DL functions show a delay on the estimation of SOS (and thus shorter LOS) with respect to SG filter. Hence, the smoothing functions from TIMESAT software should be carefully used depending on the accuracy required, as well as on the project aims and the study area.

Acknowledgements

We would like to thank the US Geological Survey for providing open access to the MODIS product and Drs Eklundh and Jönsson for providing TIMESAT software, an open source program that made this research possible. Three anonymous reviewers are also thanked for their valuable comments on how to improve the manuscript. We thank Mariana Oyarzábal for his revision of the English grammar. Besides, the authors wish to thank Comisión de Investigaciones Científicas (CIC) de la Provincia de Buenos Aires for support this work.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

The authors wish to thank Comisión de Investigaciones Científicas (CIC) de la Provincia de Buenos Aires for support this work.

References

Alcaraz-Segura, D., J. Cabello, J. M. Paruelo, and M. Delibes. 2009. "Use of Descriptors of Ecosystem Functioning for Monitoring a National Park Network: A Remote Sensing Approach." *Environmental Management* 43: 38–48. doi:10.1007/s00267-008-9154-y.

Ali, A., C. A. De Bie, A. K. Skidmore, R. G. Scarrot, and P. Lymberakis. 2014. "Mapping the Heterogeneity of Natural and Semi-Natural Landscapes." *International Journal of Applied Earth Observation and Geoinformation* 26: 176–183. doi:10.1016/j.jag.2013.06.007.

Atkinson, P. M., C. Jeganathan, J. Dash, and C. Atzberger. 2012. "Inter-Comparison of Four Models for Smoothing Satellite Sensor Time-Series Data to Estimate Vegetation Phenology." *Remote Sensing of Environment* 123: 400–417. doi:10.1016/j.rse.2012.04.001.

Atzberger, C. 2013. "Advances in Remote Sensing of Agriculture: Context Description, Existing Operational Monitoring Systems and Major Information Needs." *Remote Sensing* 5: 949–981. doi:10.3390/rs5020949.

Atzberger, C., and P. H. C. Eilers. 2011. "A Time Series for Monitoring Vegetation Activity and Phenology at 10-Daily Time Steps Covering Large Parts of South America." *International Journal of Digital Earth* 4 (5): 365–386. doi:10.1080/17538947.2010.505664.

Baldi, G., J. Guerschman, and J. M. Paruelo. 2006. "Characterizing Fragmentation in Temperate South America Grasslands." *Agriculture, Ecosystems & Environment* 116: 197–208. doi:10.1016/j.agee.2006.02.009.

Barraza, V., F. Grings, M. Salvia, P. Perna, A. E. Carbajo, and H. Karszenbaum. 2013. "Monitoring and Modelling Land Surface Dynamics in Bermejo River Basin, Argentina: Time Series Analysis of MODIS NDVI Data." *International Journal of Remote Sensing* 4 (5): 365–386.

Beck, P., C. Atzberger, K. Hogda, B. Johansen, and A. Skidmore. 2006. "Improved Monitoring of Vegetation Dynamics at Very High Latitudes: A New Method Using MODIS NDVI." *Remote Sensing of Environment* 100: 321–334. doi:10.1016/j.rse.2005.10.021.

Broich, M., A. Huete, M. G. Tulbure, X. Ma, Q. Xin, M. Paget, N. Restrepo-Coupe, K. Davies, R. Devadas, and A. Held. 2014. "Land Surface Phenological Response to Decadal Climate Variability across Australia Using Satellite Remote Sensing." *Biogeosciences* 11: 5181–5198. doi:10.5194/bg-11-5181-2014.

Burnham, K. P., and D. R. Anderson. 2002. *Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach*, 515 pp. 2nd ed. New York: Springer.

Chen, J., P. Jönsson, M. Tamura, Z. Gu, B. Matsushita, and L. Eklundh. 2004. "A Simple Method for Reconstructing A High-Quality NDVI Time-Series Data Set Based on the Savitzky–Golay Filter." *Remote Sensing of Environment* 91: 332–344. doi:10.1016/j.rse.2004.03.014.

De Castro, A. I., R. E. Plant, J. Six, and J. M. Peña. 2014. "Mapas de calendario de cultivo y variables fenológicas mediante el análisis de imágenes MODIS y ASTER basado en objetos." *Revista de Teledetección* 41: 29–36. doi:10.4995/raet.2014.2307.

de Leeuw, J., A. Vrieling, A. Shee, C. Atzberger, K. M. Hadgu, C. M. Biradar, H. Keah, and C. Turvey. 2014. "The Potential and Uptake of Remote Sensing in Insurance: A Review." *Remote Sensing* 6: 10888–10912. doi:10.3390/rs61110888.

Eastman, J. R. 2009. *Idrisi Taiga Tutorial. Earth Trends Modeler*. Wourcester, MA: Clark Labs, Clark University.

Eilers, P. H. C. 2003. "A Perfect Smoother." *Analytical Chemistry* 75: 3631–3636. doi:10.1021/ac034173t.

Eklundh, L., and P. Jönsson. 2009. *Timesat 3.0 Software Manual*. Lund: Lund University.

Gao, F., J. T. Morisette, R. E. Wolfe, G. Ederer, J. Pedelty, E. Masuoka, R. Myneni, B. Tan, and J. Nightingale. 2008. "An Algorithm to Produce Temporally and Spatially Continuous MODIS-LAI Time Series." *IEEE Geoscience and Remote Sensing Letters* 5 (1): 60–64. doi:10.1109/LGRS.2007.907971.

Herrera, L., P. Laterra, N. Maceira, K. Zelaya, and G. Martínez. 2009. "Fragmentation Status of Tall-Tussock Grassland Relicts in the Flooding Pampa, Argentina." *Rangeland Ecology & Management* 62: 73–82. doi:10.2111/08-015.

Hird, J. N., and G. J. McDermid. 2009. “Noise Reduction of NDVI Time Series: An Empirical Comparison of Selected Techniques.” *Remote Sensing of Environment* 113: 248–258. doi:10.1016/j.rse.2008.09.003.

Hmimina, G., E. Dufrêne, J.-Y. Pontailler, N. Delpierre, M. Aubinet, B. Caquet, A. de Grandcourt, et al. 2013. “Evaluation of the Potential of MODIS Satellite Data to Predict Vegetation Phenology in Different Biomes: An Investigation Using Ground-Based NDVI Measurements.” *Remote Sensing of Environment* 132: 145–158. doi:10.1016/j.rse.2013.01.010.

Holzman, M., R. Rivas, and M. Piccolo. 2014. “Estimating Soil Moisture and the Relationship with Crop Yield Using Surface Temperature and Vegetation Index.” *International Journal of Applied Earth Observation and Geoinformation* 28: 181–192. doi:10.1016/j.jag.2013.12.006.

Ivits, E., M. Cherlet, W. Mehl, and S. Sommer. 2013. “Ecosystem Functional Units Characterized by Satellite Observed Phenology and Productivity Gradients: A Case Study for Europe.” *Ecological Indicators* 27: 17–28. doi:10.1016/j.ecolind.2012.11.010.

Jakubauskas, M. E., D. R. Legates, and J. H. Kastens. 2001. “Harmonic Analysis of Time-Series AVHRR NDVI Data.” *Photogrammetric Engineering & Remote Sensing* 67 (4): 461–470.

Jin, H., and L. Eklundh. 2014. “A Physically Based Vegetation Index for Improved Monitoring of Plant Phenology.” *Remote Sensing of Environment* 152: 512–525. doi:10.1016/j.rse.2014.07.010.

Jönsson, P., and L. Eklundh. 2002. “Seasonality Extraction by Function-Fitting to Time Series of Satellite Sensor Data.” *IEEE Transactions on Geoscience and Remote Sensing* 40: 1824–1832. doi:10.1109/TGRS.2002.802519.

Jönsson, P., and L. Eklundh. 2004. “Timesat – a Program for Analyzing Time-Series of Satellite Sensor Data.” *Computers & Geosciences* 30: 833–845. doi:10.1016/j.cageo.2004.05.006.

Kogan, F. N. 1997. “Global Drought Watch from Space.” *Bulletin of the American Meteorological Society* 78 (4): 621–636. doi:10.1175/1520-0477(1997)078<0621:GDWFS>2.0.CO;2.

Lara, B., and M. Gandini. 2014. “Quantifying the Land Cover Changes and Fragmentation Patterns in the Argentina Pampas, in the Last 37 Years (1974-2011).” *Geofocus (Artículos)* 14: 163–180.

Leinenkugel, P., C. Kuenzer, N. Oppelt, and S. Dech. 2013. “Characterisation of Land Surface Phenology and Land Cover Based on Moderate Resolution Satellite Data in Cloud Prone Areas — A Novel Product for the Mekong Basin.” *Remote Sensing of Environment* 136: 180–198. doi:10.1016/j.rse.2013.05.004.

Li, Z., T. Huffman, A. Zhang, F. Zhou, and B. McConkey. 2012. “Spatially Locating Soil Classes within Complex Soil Polygons – Mapping Soil Capability for Agriculture in Saskatchewan Canada.” *Agriculture, Ecosystems & Environment* 152 (5): 59–67. doi:10.1016/j.agee.2012.02.007.

Liu, J., X. Yang, H. Liu, and Z. Qiao. 2013. “Algorithms and Applications in Grass Growth Monitoring.” *Abstract and Applied Analysis* 2013: 7 p.

Matteucci, S. 2012. “Ecorregión Pampa.” In *Ecorregiones y Complejos Ecosistémicos Argentinos*, edited by J. Morello, S. Matteucci, A. Rodríguez, and M. Silva, 391–446. Buenos Aires: Orientación Gráfica Editora.

Melendez-Pastor, I., J. Navarro-Pedreño, M. Koch, I. Gómez, and E. I. Hernández. 2010. “Land-Cover Phenologies and Their Relation to Climatic Variables in an Anthropogenically Impacted Mediterranean Coastal Area.” *Remote Sensing* 2: 697–716. doi:10.3390/rs2030697.

Monteith, J. L. 1981. “Climatic Variation and the Growth of Crops.” *Quarterly Journal of the Royal Meteorological Society* 107 (454): 749–774. doi:10.1002/qj.49710745402.

Moody, A., and D. M. Johnson. 2001. “Land-Surface Phenologies from AVHRR Using the Discrete Fourier Transform.” *Remote Sensing of Environment* 75: 305–323. doi:10.1016/S0034-4257(00)00175-9.

Paruelo, J. M., H. E. Epstein, W. K. Lauenroth, and I. C. Burke. 1997. “ANPP Estimates from NDVI for the Central Grassland Region of the United States.” *Ecology* 78 (3): 953–958. doi:10.1890/0012-9658(1997)078[0953:AEFNFT]2.0.CO;2.

Paruelo, J. M., E. G. Jobbágy, and O. E. Sala. 2001. “Current Distribution of Ecosystem Functional Types in Temperate South America.” *Ecosystems* 4: 683–698. doi:10.1007/s10021-001-0037-9.

Pettorelli, N., J. Vik, A. Mysterud, J. Gaillard, C. Tucker, and N. Stenseth. 2005. “Using the Satellite-Derived NDVI to Assess Ecological Responses to Environmental Change.” *Trends in Ecology & Evolution* 20 (9): 503–510. doi:10.1016/j.tree.2005.05.011.

Rembold, F., C. Atzberger, I. Savin, and O. Rojas. 2013. “Using Low Resolution Satellite Imagery for Yield Prediction and Yield Anomaly Detection.” *Remote Sensing* 5: 1704–1733. doi:10.3390/rs5041704.

Solano, R., K. Didan, A. Jacobson, and A. Huete. 2010. *MODIS Vegetation Index User’s Guide (MOD13 Series) C5*. Tucson: Vegetation Index and Phenology Lab, The University of Arizona.

Tan, B., J. Morisette, R. Wolfe, F. Gao, G. Ederer, J. Nightingale, and J. Pedelty. 2011. “An Enhanced TIMESAT Algorithm for Estimating Vegetation Phenology Metrics from MODIS Data.” *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 4 (2): 361–371. doi:10.1109/JSTARS.2010.2075916.

Tucker, C. J., and B. J. Choudhury. 1987. “Satellite Remote Sensing of Drought Conditions.” *Remote Sensing of Environment* 23: 243–251. doi:10.1016/0034-4257(87)90040-X.

van Leeuwen, W., K. Hartfield, M. Miranda, and F. J. Meza. 2013. “Trends and ENSO/AAO Driven Variability in NDVI Derived Productivity and Phenology alongside the Andes Mountains.” *Remote Sensing* 5: 1177–1203. doi:10.3390/rs5031177.

Vega, E., G. Baldi, E. Jobbágy, and J. Paruelo. 2009. “Land Use Change Patterns in the Rio de La Plata Grasslands: The Influence of Phytogeographic and Political Boundaries.” *Agriculture, Ecosystems & Environment* 134: 287–292. doi:10.1016/j.agee.2009.07.011.

Viglizzo, E., F. Lértora, A. Pordomingo, J. Bernardos, Z. Roberto, and H. Del Valle. 2001. “Ecological Lessons and Applications from One Century of Low External-Input Farming in the Pampas of Argentina.” *Agriculture, Ecosystems & Environment* 83: 65–81. doi:10.1016/S0167-8809(00)00155-9.

Wang, Q., J. Tenhunen, N. Q. Dinh, M. Reichstein, T. Vesala, and P. Keronen. 2004. “Similarities in Ground- and Satellite-Based NDVI Time Series and Their Relationship to Physiological Activity of a Scots Pine Forest in Finland.” *Remote Sensing of Environment* 93 (1–2): 225–237. doi:10.1016/j.rse.2004.07.006.

White, M. A., K. M. de Beurs, K. Didan, D. W. Inouye, A. D. Richardson, O. P. Jensen, J. O’Keefe, et al. 2009. “Intercomparison, Interpretation, and Assessment of Spring Phenology in North America Estimated from Remote Sensing for 1982-2006.” *Global Change Biology* 15: 2335–2359. doi:10.1111/gcb.2009.15.issue-10.

Wolter, K., and M. S. Timlin. 2011. “El Niño/Southern Oscillation Behaviour since 1871 as Diagnosed in an Extended Multivariate ENSO Index (Mei.Ext).” *International Journal of Climatology* 31: 1074–1087. doi:10.1002/joc.v31.7.

Yang, Y., J. Xu, Y. Hong, and G. Lv. 2012. “The Dynamic of Vegetation Coverage and Its Response to Climate Factors in Inner Mongolia, China.” *Stochastic Environmental Research and Risk Assessment* 26: 357–373. doi:10.1007/s00477-011-0481-9.

Zhu, L., and J. Meng. 2015. “Determining the Relative Importance of Climatic Drivers on Spring Phenology in Grassland Ecosystems of Semi-Arid Areas.” *International Journal of Biometeorology* 59: 237–248. doi:10.1007/s00484-014-0839-z.