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Smoothing and gap-filling of high resolution multi-spectral time series: Example of Landsat data

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ABSTRACT

This paper introduces a novel methodology for generating 15-day, smoothed and gap-filled time series of high spatial resolution data. The approach is based on templates from high quality observations to fill data gaps that are subsequently filtered. We tested our method for one large contiguous area (Bavaria, Germany) and for nine smaller test sites in different ecoregions of Europe using Landsat data. Overall, our results match the validation dataset to a high degree of accuracy with a mean absolute error (MAE) of 0.01 for visible bands, 0.03 for near-infrared and 0.02 for short-wave-infrared. Occasionally, the reconstructed time series are affected by artefacts due to undetected clouds. Less frequently, larger uncertainties occur as a result of extended periods of missing data. Reliable cloud masks are highly warranted for making full use of time series.

1. Introduction

An increasing number of analytical and methodological tools, applications and services require continuous and frequently updated Earth Observation (EO) time series data. Examples are land surface phenology (Verbesselt et al., 2010a; Verbesselt et al., 2010b; Melaas et al., 2013), agricultural monitoring systems (Moran et al., 1997), crop yield mapping and prediction (Unganai and Kogan, 1998; Rembold et al., 2013), irrigation management (Vuolo et al., 2015a; Vuolo et al., 2015c), mapping of crop types (Wardlow et al., 2007) and cropping systems (Sakamoto et al., 2006; El Hajj et al., 2009). The opportunities for exploiting time series improved radically in 2008 when the Landsat program opened its more than 40 years archive (Woodcock et al., 2008). Further improvements are expected thanks to the European Copernicus program (Berger et al., 2012). Its first optical high resolution satellite (Sentinel-2A) was successfully launched on April 27th 2015 and a twin satellite will follow in early 2017 (Sentinel-2B).

One main limiting factor for full exploitation of these high spatial resolution optical time series relates to data gaps and noise due to clouds, cloud shadow and snow cover. Impacts depend on season, topography, location and environment (e.g. mountainous and coastal areas with usually less usable data) (Beck et al., 2006; Ju and Roy, 2008). Various approaches attempted to reconstruct EO data to obtain high resolution cloud- and gap-free images using temporal composited mosaicking (Bielski et al., 2007; Roy et al., 2010; Eivazi et al., 2015; Lei and Siqueira, 2015), histogram matching (Helmer and Ruefenacht, 2005; Rakwatin et al., 2007; Shapira et al., 2013), pixel based compositing (Griffiths et al., 2013; Hermosilla et al., 2015a; Vanonckelen et al., 2015; Zhu et al., 2015a), data fusion (Gao et al., 2006; Roy et al., 2008; Hilker et al., 2009; Zhang et al., 2013; Bisquert et al., 2015; Gevaert and García-haro, 2015) and spatial-temporal gap-filling (Xu et al., 2015; Malambo and Heatwole, 2016). A review can be found in (Shen et al., 2015). These approaches are often applied to gap-fill time series of spectral indices and frequently do not provide sufficient temporal resolution (e.g. 15-day) to study highly dynamic crop growing conditions at high spatial resolution (i.e. 30 m with Landsat).

The scope of this paper is to introduce a novel methodology to create spatially and temporally consistent and continuous time series of cloud-free, bottom-of-the-atmosphere (BOA) multispectral images at high spatial and temporal resolution. To develop and validate the methodology, we use Landsat data and compare reconstructed images against non-cloudy reference data not used during the filtering and gap-filling process.

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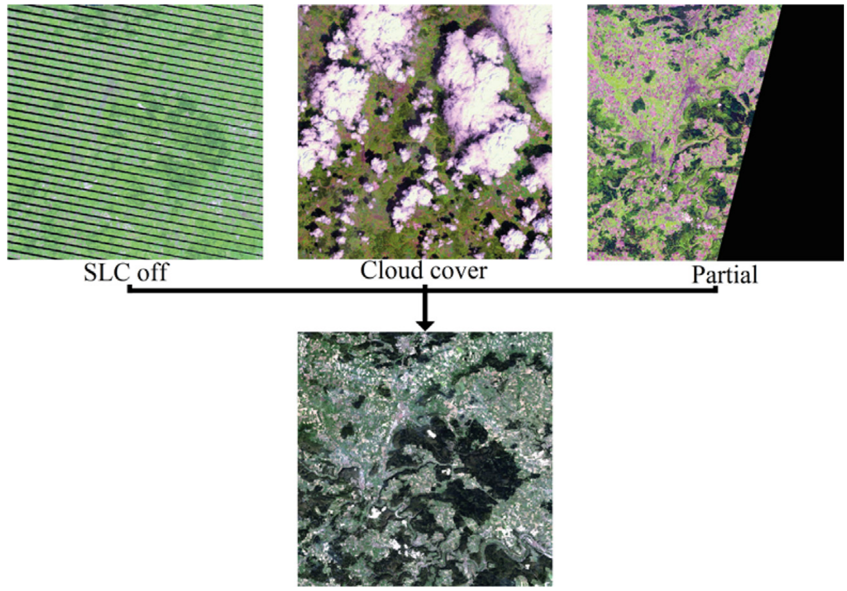

Fig. 1. Illustration of the main radiometric problems occurring when working with high spatial resolution data, hindering the generation of high quality time series.

2. Material and methods

The proposed methodology is applied on temporal stacks of Landsat data, where the data cube includes layers being (partially) cloudy and/or showing sensor artefacts (Fig. 1). The novelty of the proposed approach stems from two innovative aspects:

- the filling of data gaps using templates (e.g. information derived from the neighbourhood of the pixel to be filtered) complementing the available data where missing, and
- the use of a state-of-the-art Whittaker smoother for filtering the previously gap-filled time series.

The methodological workflow to produce smooth and gap-filled images is presented in Fig. 2 and the key elements are illustrated in Fig. 3 for one exemplary pixel in two spectral channels.

In the first step, Landsat data are clipped in image tiles of equal size (1000 × 1000 pixels) preserving the native pixel size, geographic projection (UTM WGS 84) and day of acquisition. Then, in a second step, a mask is constructed, which is used to weight each observation in the subsequent filtering process. For the construction of this mask, an essential requirement is the identification of data gaps. We rely on the *Function of mask* (‘fmask’) algorithm, part of the Landsat production chain, to flag clouds, cloud shadows and snow pixels (Zhu et al., 2015b). Our binary mask takes a value of w = 1 (i.e. valid observations) for non-cloudy and non-missing values and a value of w = 0 (not valid observations) for all other pixels (including snow).

The data is transformed in a third step into equally spaced observations with a temporal resolution of 15 days resulting in 24 regularly spaced images per year (2 images per month). The date of the first day of the compositing period is assigned to the new images (e.g. 1st and 16th of each month). If two (or more) valid observations for the same pixel are found within a 15-day period, the average is calculated and used; the mask value remains at w = 1 (valid observation). Note that gaps are still present in these composite images.

The forth step consists in building a pool of so-called ‘templates’. Templates are time series of pixels characterized by a high number of valid observations in the temporal dimension. Before making use of the templates for gap-filling, gaps in the templates are filled

Table 1
Overview of parameters and recommended settings.

Parameter	Description	Min.	Max	Standard value
λ_{WS}	Smoothing parameter of the Whittaker filter	1	9	3
w	Weight assigned to: cloudy pixels			0
	clear pixels			1
wt	Weight assigned to templates	0.1	0.7	0.5
n_T	Number of considered templates	500	1000	500
tpp	Templates considered per pixel	1	5	5

using the Whittaker smoother developed by Eilers (Eilers, 2003) (a weighted spline with second order finite difference penalty) and a smoothing parameter (λ_{WS} = 0.5) that preserves fidelity to data rather than data smoothness (Atzberger and Eilers, 2011) (Eq. (1)). The template selection is performed considering multiple years in the temporal stack of 15-day images (e.g. 2009–2016). To ensure representativeness of the templates, the template search is stratified using the CORINE land cover map (European Environment Agency, 2006) aggregated to 11 classes (Table 3). Within each class, we first count the total number of valid observations per pixel and the length of data gaps and then select the pixels with the highest number of valid observations and the most regular distribution of gaps (e.g. avoiding clumped – and therefore long – data gaps). For this study, to qualify as template, the number of valid observations should be greater than the 99th percentile of the valid observations in a specific image tile and the variance in the length of data gaps should be less than the 1st percentile. Amongst the candidates that satisfy these two rules (quantity of valid observations and distribution of gaps), we exclude the most similar templates based on the pair-wise Euclidean distance ensuring that at least 50% of the pairs have a distance below the total mean distance of the overall distance matrix.

The fifth step is the ‘template matching’. During this step we compute the Euclidean distance between each template and each pixel and then select the templates that best match the temporal and spectral profile of each pixel. The Euclidean distance is calculated considering all spectral bands and temporal dimensions