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Spatio-temporal fusion for daily Sentinel-2 images

Qunming Wang[a,b], Peter M. Atkinson[a,c,d,*]

[a] Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ, UK
[b] Centre for Ecology & Hydrology, Lancaster LA1 4YQ, UK
[c] Geography and Environment, University of Southampton, Highfield, Southampton SO17 1BJ, UK
[d] School of Geography, Archaeology and Palaeoecology, Queen's University Belfast, BT7 1NN, Northern Ireland, UK

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ABSTRACT

Sentinel-2 and Sentinel-3 are two newly launched satellites for global monitoring. The Sentinel-2 Multispectral Imager (MSI) and Sentinel-3 Ocean and Land Colour Instrument (OLCI) sensors have very different spatial and temporal resolutions (Sentinel-2 MSI sensor 10 m, 20 m and 60 m, 10 days, albeit 5 days with 2 sensors, conditional upon clear skies; Sentinel-3 OLCI sensor 300 m, < 1.4 days with 2 sensors). For local monitoring (e.g., the growing cycle of plants) one either has the desired spatial or temporal resolution, but not both. In this paper, spatio-temporal fusion is considered to fuse Sentinel-2 with Sentinel-3 images to create nearly daily Sentinel-2 images. A challenging issue in spatio-temporal fusion is that there can be very few cloud-free fine spatial resolution images temporally close to the prediction time, or even available, strong temporal (i.e., seasonal) changes may exist. To this end, a three-step method consisting of regression model fitting (RM fitting), spatial filtering (SF) and residual compensation (RC) is proposed, which is abbreviated as Fit-FC. The Fit-FC method can be performed using only one Sentinel-3–Sentinel-2 pair and is advantageous for cases involving strong temporal changes (i.e., mathematically, the correlation between the two Sentinel-3 images is small). The effectiveness of the method was validated using two datasets. The created nearly daily Sentinel-2 time-series images have great potential for timely monitoring of highly dynamic environmental, agricultural or ecological phenomena.

1. Introduction

Sentinel-2 is a new program of the European Space Agency (ESA) for fine spatial resolution global monitoring (Drusch et al., 2012; Hagolle et al., 2015; Segl et al., 2015). The Sentinel-2A and -2B satellites were launched on 23 June 2015 and 7 March 2017, respectively. The twin satellites are in the same orbit and 180° apart from each other and they are now releasing data routinely. The Sentinel-2 Multispectral Imager (MSI) provides 13 spectral bands in the visible, near infrared (NIR) and short wave infrared (SWIR) wavelengths, with four bands at 10 m (centered at 490 nm, 560 nm, 665 nm and 842 nm), six bands at 20 m (centered at 705 nm, 740 nm, 783 nm 865 nm, 1610 nm, and 2190 nm) and three bands at 60 m spatial resolution (centered at 443 nm, 940 nm and 1375 nm) (Drusch et al., 2012; Du et al., 2016; Hagolle et al., 2015; Wang et al., 2016). The Sentinel-2 data can be used to support global land services including monitoring vegetation, soil and water cover, etc. Such data are receiving increasing attention in remote sensing studies and applications (Fernández-Manso et al., 2016; Immitzer et al., 2016; Novelli et al., 2016; Storey et al., 2016; Van der Werff and Van der Meer, 2016). The Sentinel-2A or -2B satellite can revisit the same area every 10 days (5 days with the twin satellites together). Due to cloud and shadow contamination, however, it generally requires > 5 days (e.g., probably several months) to acquire a cloud-free Sentinel-2 image for specific areas. The temporally sparse Sentinel-2 observations, especially for areas that can be easily covered by clouds, are not sufficient for monitoring rapid changes such as growing cycle of plants.

Sentinel-3, another very new program of the ESA, is a satellite imaging mission designed for global monitoring for environment and security (GMES) to ensure frequent and near real-time measurements to ocean, land, and atmospheric services (Berger and Aschbacher, 2012; Donlon et al., 2012; Verhoef and Bach, 2012). The Sentinel-3A satellite was launched on 16 February 2016. The instrument of the satellite includes a Sea and Land Surface Temperature Radiometer (SLSTR), a Synthetic Aperture Radar Altimeter (SRAL) and an Ocean and Land Colour Imager (OLCI). The OLCI sensor delivers 21-band wide-swath optical images at a temporal resolution of < 2.8 days (will be increased to < 1.4 days after the launch of the twin satellite Sentinel-3B). Compared to Sentinel-2 MSI, Sentinel-3 OLCI can provide data more frequently for timely monitoring. However, the Sentinel-3 OLC images are at a much coarser spatial resolution of 300 m. Such a spatial resolution

* Corresponding author at: Lancaster Environment Centre, Lancaster University, Lancaster LA1 4YQ, UK.
E-mail address: pma@lancaster.ac.uk (P.M. Atkinson).

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Table 1
The corresponding bands for Sentinel-2 MSI and Sentinel-3 OLCI images.

Sentinel-2			Sentinel-3		
Band number	Wavelength (nm)	Spatial resolution (m)	Band number	Wavelength (nm)	Spatial resolution (m)
2 (blue)	458–523	10	Oa4 (blue)	437–447	300
3 (green)	543–578	10	Oa6 (green)	555–565	300
4 (red)	650–680	10	Oa8 (red)	660–670	300
8a (NIR)	855–875	20	Oa17 (NIR)	855–875	300

is too coarse to provide sufficient detail for local areas of interest.

There is a great need for data that have simultaneously the spatial resolution of Sentinel-2 (10 m) and temporal resolution of Sentinel-3 (i.e., nearly daily Sentinel-2 time-series) to provide more informative data and support a wider range of monitoring applications, particularly for areas where the amount of available effective Sentinel-2 observations is limited due to cloud contamination. The daily Sentinel-2 images have great value for dynamic monitoring of rapid changes on the Earth's surface at a required fine spatial resolution, such as timely crop monitoring (Gao et al., 2017). Both Sentinel-2 MSI and Sentinel-3 OLCI data are freely available to users and have global coverage. Furthermore, the two sensors have the similar wavelengths for four bands (i.e., blue, green, red and NIR bands), as shown in Table 1. In our previous study Wang et al. (2016), an accurate method based on area-to-point regression kriging (ATPRK) (Wang et al., 2015) was used to fuse the 20 m Sentinel-2 8a band with 10 m bands 2, 3, 4 and 8 to produce 10 m Sentinel-2 8a. This provides an excellent opportunity for spatio-temporal fusion of 10 m Sentinel-2 MSI and 300 m Sentinel-3 OLCI data to create 10 m, daily Sentinel-2 images. With this process, the number of cloud-free Sentinel-2 images, as well as the temporal resolution, can be maximized.

Spatio-temporal fusion approaches have been developed for blending fine spatial resolution, but coarse temporal resolution Landsat and fine temporal resolution, but coarse spatial resolution Moderate Resolution Imaging Spectroradiometer (MODIS) or MEdium Resolution Imaging Spectrometer (MERIS) images to create fine spatio-temporal resolution images (Gao et al., 2015; Zhang et al., 2015; Chen et al., 2015). The implementation requires at least one coarse-fine spatial resolution image pair (e.g., MODIS-Landsat image pair acquired on the same day) or one fine spatial resolution image (hereafter called fine image) that is temporally close to the prediction day. In recent years, several spatio-temporal fusion approaches have been developed. The spatial and temporal adaptive reflectance fusion model (STARFM) is one of the earliest and most widely used spatio-temporal fusion approaches (Gao et al., 2006). Appreciating its simple implementation, it has been used to support various applications, such as forest monitoring, crop monitoring (Gao et al., 2015; Gao et al., 2017), leaf area index (LAI) monitoring (Dong et al., 2016; Houborg et al., 2016), land surface temperature (LST) monitoring (Shen et al., 2016) and gross primary productivity (GPP) monitoring (Singh, 2011). STARFM is performed based on the availability of at least one image-pair. It assumes that the temporal changes of all classes within a coarse pixel are uniform, which is more suitable for homogeneous landscape dominated by pure coarse pixels. To enhance the performance of STARFM for heterogeneous landscapes dominated by mixed pixels, an enhanced STARFM (ESTARFM) method was developed (Zhu et al., 2010). Based on the availability of two coarse-fine image pairs, ESTARFM estimates the temporal change rate of each class separately and assumes the change rates to be stable during a period (Emelyanova et al., 2013). STARFM was also extended for timely monitoring of forest disturbance based on a version termed spatial temporal adaptive algorithm for mapping reflectance change (STAARCH) (Hilker et al., 2009). Based on the mechanism of machine learning, some learning-based methods were proposed, including sparse representation (Huang and Song, 2012; Song and Huang, 2013), extreme learning machine (Liu et al., 2016), artificial neural network and support vector regression (Moosavi et al., 2015), and deep learning (Das and Ghosh, 2016). This type of method learns the relationship between the available coarse-fine image pairs, which is used to guide the prediction of fine images from coarse images on other days.

Alternatively, spatial unmixing is a type of spatio-temporal fusion approach that can be performed using one fine image. More precisely, it requires a fine spatial resolution thematic map that can be derived by interpretation of the available fine spatial resolution data (Amorós-López et al., 2011, 2013; Gevaert and García-Haro, 2015; Zurita-Milla et al., 2008) or from other sources including an aerial image (Mustafa et al., 2014), or land-use database (Zurita-Milla et al., 2009). Different from spectral unmixing which estimates for which the class proportions within coarse pixels and where the class endmembers (spectra) are known, spatial unmixing estimates the class endmembers within coarse pixels and the class proportions are known (calculated by upscaling the fine spatial resolution thematic map) (Busetto et al., 2008; Maselli, 2001; Zhukov et al., 1999). Spatial unmixing assumes that no land-cover/land-use changes occur during the period of interest and the class proportions are constant for coarse images at different times. This approach was used to create 30 m Landsat-like time-series from 300 m MERIS images using a 30 m thematic map obtained by classification of an available Landsat image (Zurita-Milla et al., 2008) or a fine spatial resolution land-use database LGN5 (Zurita-Milla et al., 2009). Wu et al. (2012) extended spatial unmixing to cases with one coarse-fine image pair available and proposed a surface reflectance calculation model (SRCM). SRCM performs unmixing separately for two coarse images and estimates the temporal changes of each endmember spectra and finally adds the changes to the known fine image. Similarly to the idea of SRCM, Gevaert and García-Haro (2015) performed unmixing directly for the residual image (defined as the difference between two coarse images) to estimate the changes of endmember spectra. Huang and Zhang (2014) developed an unmixing-based spatio-temporal reflectance fusion model (U-STFM) using two coarse-fine image pairs. The spatial unmixing approach can also be combined with STARFM and some hybrid methods were developed (Xu et al., 2015; Xie et al., 2016; Zhu et al., 2016).

For spatio-temporal fusion in practice, one challenging problem is that sometimes very few fine images (Sentinel-2 image in this paper) that are temporally close to the prediction time are available for use, due to cloud and shadow contamination. Another problem is that even where one fine image is available, strong temporal changes may have occurred from the time of the fine image to prediction. This means that the observations at two times may be very different and do not have a strong correlation. This is exacerbated for the fusion of 10 m Sentinel-2 MSI and 300 m Sentinel-3 OLCI images, which involves a large zoom factor of 30 (double of that from 500 m MODIS to 30 m Landsat spatial resolution) and a number of mixed pixels. In this case, the available fine image on one day may be very different to the ideal prediction on another day. Thus, how to make full use of the available fine image is a critical issue. The U-STFM (Huang and Zhang, 2014) and flexible spatiotemporal data fusion (FSDAF) (Zhu et al., 2016) methods were developed to deal with strong temporal changes. However, U-STFM requires at least two coarse-fine image pairs. Although FSDAF requires only one image pair, its performance may sometimes be compromised by the unmixing process where a global, linear unmixing model is considered.

In this paper, to cope with the abovementioned problems, we propose a new method for fusion of Sentinel-2 MSI and Sentinel-3 OLCI images. The new method consists of three stages, including regression model fitting (RM fitting, hereafter called RM), spatial filtering (SF) and

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