Science of the Total Environment 633 (2018) 677–683

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Filling the missing data gaps of daily MODIS AOD using spatiotemporal interpolation

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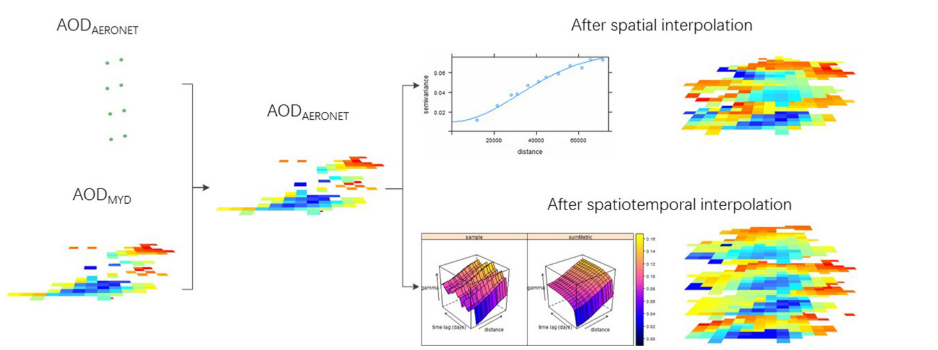
HIGHLIGHTS

- We produced a gap-filling daily MODIS AOD product based on spatiotemporal kriging.
- The completeness of product was significantly improved from 14.27% to 67.73%.
- The spatiotemporal kriging performed better and more stable than spatial kriging interpolation method.
- The AOD distribution in Beijing had typical seasonal variations that were highly related to topography.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 7 November 2017
Received in revised form 15 March 2018
Accepted 18 March 2018
Available online xxxx

Editor: Jianmin Chen

Keywords:
MODIS aerosol product
Spatiotemporal correlation
Missing AOD data
Interpolation

ABSTRACT

Aerosol is an important component of the atmosphere that affects the environment, climate, and human health. Remote sensing is an efficient observation method for monitoring global aerosol distribution and changes over time. The daily Moderate Resolution Imaging Spectroradiometer (MODIS) level-2 aerosol optical depth (AOD) (Collection 6) product (10 km resolution) is often used to study climate change and air pollution. However, the product is prone to yielding large amounts of data gaps due to the unfeasibility of retrieving reliable estimates under cloudy conditions, and these data gaps inevitably affect the results and analysis of the product's application. In this study, a geostatistical data interpolation framework based on the spatiotemporal kriging method was implemented to interpolate satellite AOD products in Beijing, China. Compared to the ordinary kriging method for filling data gaps, the spatiotemporal interpolation not only utilizes spatial autocorrelation but also considers the temporal and spatiotemporal autocorrelations between different locations. In the study region, the completeness of the spatiotemporal-interpolated AOD product reaches 67.73%, which is significantly superior to the completeness of the original MODIS product (14.27%) and that of the spatial kriging-interpolated AOD product (33.3%). The cross-validation results show that the mean absolute error of the spatiotemporal kriging results (0.07) is lower than that of the ordinary kriging (0.09).

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https://doi.org/10.1016/j.scitotenv.2018.03.202

1. Introduction

Aerosols are solid and/or liquid particles suspended in the air, such as dust, smoke, and haze (Chin, 2009). Both natural and human processes contribute to aerosol concentrations, which directly and indirectly affect climate (Flato et al., 2013). The direct effect of aerosols on climate involves scattering and absorption of radiation, while the indirect effect occurs by modifying the optical properties and lifetimes of clouds (Ramachandran, 2007). In fact, radiation changes in the earth's climate system do not always lead to global warming; aerosol is also the main factor in global cooling (Chin, 2009). Aerosol loading, or the amount of aerosol in the atmosphere, is usually quantified by mass concentration or by an optical measure, such as aerosol optical depth (AOD), which is the vertical integral of aerosol extinction coefficients along the entire height of the atmosphere (Tang et al., 2016).

The AOD can be determined using satellite-based observations and ground-based observations (Chen et al., 2016). The Aerosol Robotic Network (AERONET) is one of the most important ground-based aerosol monitoring networks in the world and provides reliable temporal continuous AOD values. However, because of the limited number of monitoring sites, it is difficult to carry out a regional, small-scale area analysis (Liu et al., 2004). Satellite-based observations, such as the Moderate Resolution Imaging Spectroradiometer (MODIS), have been widely used in the study of aerosol radiative forcing to monitor regional and global climate because of their high spatial resolution and global coverage, which sufficiently make up for the sparsely distributed ground-monitoring sites of the AERONET (Qi et al., 2013). However, the satellite AOD algorithm relies on specific conditions, such as the absence of clouds: if the satellite is covered by clouds, then it will produce more data gaps (Kokhanovsky et al., 2007). When relying on appropriate surface conditions under dark conditions, the inversion results will be poor in the desert or near the coast (Remer et al., 2005). These large numbers of data gaps limit the applicability of the product to air quality monitoring and forecasting.

Several researchers have attempted to fill the AOD data gaps by fusing datasets from different sources. Other researchers have calculated the monthly mean or used scale coarsening to ignore the data gaps (Chatterjee et al., 2010; Chen and Tian, 2010; Papadimas et al., 2008). However, ignoring the data gaps may result in inaccurate analysis, especially in high-concentration areas. Although some scholars have proposed a variety of cloud removal algorithms for satellite-based observations, information on aerosol in thick clouds tends to be difficult to retrieve due to the instability of the aerosol distribution in such clouds (Sahoo and Patnaik, 2008). Several attempts have been made to merge multi-sensor AOD. Singh et al. (2016) developed an interpolated AOD product based on MODIS and Multi-angle Imaging SpectroRadiometer (MISR) AOD datasets using a Bayesian model. However, the spatial resolution of the interpolated AOD dataset was $0.25° \times 0.25°$, and this resolution value makes it difficult to meet fine-scale air quality monitoring needs. Tang et al. (2016) developed a spatiotemporal, statistical data fusion framework based on the Bayesian maximum entropy method. The mean spatiotemporal completeness of AOD was improved to 95.2%, and the validation results were also rather good. However, the large computation requirement may limit its application in large areas and long time series. Ruiz-Arias et al. (2013) presented a geostatistical methodology for reducing bias and removing data gaps for a daily gridded AOD dataset with a resolution of $1° \times 1°$. Van Donkelaar et al. (2010) developed an approach for combining MODIS and MISR AOD into a single improved estimate of AOD. Chatterjee et al. (2010) applied the universal kriging method to average AOD from MISR, MODIS, and AERONET to achieve high-precision AOD products. Although the spatial interpolation method works rather well, temporal correlation was not considered in the research. Actually, similar to meteorological elements (Hengl et al., 2012), AOD distribution can be treated as a typical spatiotemporal random field. An efficient spatiotemporal AOD gap-filling model that contains different aspects of correlation and requires considerable computation is necessary for applications in large areas.

In this study, we present a procedure to interpolate daily MODIS level-2 AOD (Collection 6) over a one-year period using the spatiotemporal (ST) kriging method. The MODIS level-2 AOD product files of the Beijing area for the entire calendar year of 2014 were collected from both the Terra and Aqua satellites. First, we examined the correlation between the MODIS AOD and the AERONET AOD. After that, we calibrated the former data with that of the latter using a linear regression model. Then, the calibrated MODIS AOD data was modeled using the spatiotemporal kriging method. Finally, the results of the interpolation were validated by 10-fold cross validation and compared with the results of the spatial ordinary kriging (OK) method.

2. Data and methods

2.1. Study area

Beijing is the political and cultural center of China, with a population of >21.5 million (Zhang and Wu, 2018). The north and west of Beijing are surrounded by mountains, which means that Beijing is in a “dustpan” pocket. When monsoons occur in the southeast, the atmosphere in the region does not circulate easily. Moreover, the city is surrounded by large numbers of industrial exhaust emissions. Therefore, Beijing's atmosphere has a strong aerosol concentration (Tang et al., 2016).

2.2. Data

2.2.1. MODIS level-2 AOD

The MODIS sensor is part of the 1991 NASA-initiated Earth observation system, which was established with the aims of monitoring the global environmental and climate change and observing and preventing large-scale natural disasters. The MODIS level-2 AOD data (C6) (10 km resolution) of the Beijing area for the entire calendar year of 2014 were collected from both the Terra and Aqua satellites in this study. The Terra satellite is timed to cross the equator from north to south at about 10:30 am local time, while the Aqua satellite is timed to cross the equator from south to north at about 1:30 pm local time. In this research, AOD products from the Terra and the Aqua satellites are labeled as AOD_{MOD} and AOD_{MYD}, respectively. The product can be obtained through a variety of free channels (https://ladsweb.nascom.nasa.gov/data/search.html), one of which was used as a data source for this study (Ma et al., 2014). ENVI IDL programs were developed to read the MODIS HDF files and to extract the AOD at 550 nm over land.

2.2.2. AERONET

The AERONET AOD observation data were obtained from https://aeronet.gsfc.nasa.gov/.html. There are two sites in Beijing (Fig. 1). The AERONET aerosol product includes three levels of datasets (level 1, level 1.5, and level 2). The level 1 products are unprocessed data, the level 1.5 products are cloud-screened data, and the level 2 products are quality assured data (Singh et al., 2016). The level 2 data were used in this research. Because the AERONET site does not contain the AOD in a 550 nm band, we derived the AERONET AOD values at 550 nm by interpolating the AOD in 440 nm and 675 nm bands to be compatible with MODIS AOD products using the following equation (Liu et al., 2004).

$$\begin{aligned} \tau_{550} &= \tau_{\lambda 2} \times \left(\frac{\lambda 3}{\lambda 2}\right)^{-\alpha_{\lambda 1 \sim \lambda 2}} \\ \alpha_{\lambda 1 \sim \lambda 2} &= -\frac{\ln(\tau_{\lambda 1}/\tau_{\lambda 2})}{\ln(\lambda 1/\lambda 2)}, \end{aligned} \tag{1}$$

where $\tau_{\lambda 1}$ and $\tau_{\lambda 2}$ are AOD values at the wavelengths of $\lambda 1$ (440 nm) and $\lambda 2$ (675 nm). The spectral interpolation and extraction processes of the AERONET data were batch processed using R software.