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Retrieval of dust storm aerosols using an integrated Neural Network model

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ABSTRACT

Dust storms are known to have adverse effects on public health. Atmospheric dust loading is also one of the major uncertainties in global climatic modeling as it is known to have a significant impact on the radiation budget and atmospheric stability. This study develops an integrated model for dust storm detection and retrieval based on the combination of geostationary satellite images and forward trajectory model. The proposed model consists of three components: (i) a Neural Network (NN) model for near real-time detection of dust storms; (ii) a NN model for dust Aerosol Optical Thickness (AOT) retrieval; and (iii) the Hybrid Single Particle Lagrangian Integrated Trajectory (HYSPLIT) model to analyze the transports of dust storms. These three components are combined using an event-driven active geo-processing workflow technique. The NN models were trained for the dust detection and validated using sunphotometer measurements from the AErosol RObotic NETwork (AERONET). The HYSPLIT model was applied in the regions with high probabilities of dust locations, and simulated the transport pathways of dust storms. This newly automated hybrid method can be used to give advance near real-time warning of dust storms, for both environmental authorities and public. The proposed methodology can be applied on early warning of adverse air quality conditions, and prediction of low visibility associated with dust storm events for port and airport authorities.

1. Introduction

Approximately 800 Tg of dust are released from the arid and semiarid regions of northwestern China every year (Zhang et al., 1997). Asian dust transport is usually associated with frontal systems and/or cyclones (Tsai et al., 2008). Dust particles are most commonly transported by northwesterly winds near the surface under Asian winter monsoonal conditions and by westerly winds in the free troposphere from the eastern Asian continent out over the Pacific Ocean (Zhao et al., 2006). Many previous articles and reports have described the transport of Asian dust to downwind areas, including South Korea (Tatarov et al., 2012), Japan (Var et al., 2000), Taiwan (Lin, 2001), Hong Kong (Wong et al., 2010), India (Badarinath et al., 2007, 2008, 2009), and Arabian Sea (Badarinath et al., 2010). It is also known that dust aerosols have serious adverse impacts on human health (Chan et al., 2007). The chemical dioxins, anthropogenic inorganic pollutants, and trace metals, as well as the associated pathogenic fungi and bacteria may attach to dust particles when dust storms pass through the urbanized and industrialized regions (Garrison et al., 2003). In addition, the atmospheric impact of Asian dusts has also been extensively studied (Husar et al., 2001; McKendry et al., 2001; Zhao et al., 2008). Atmospheric mineral-dust loadings can affect the earth's radiation budget leading to a reduction of 30–40% in solar radiation, as well as in visibility; they may also promote the formation of severe haze (Husar et al., 2001; Akhlaq et al., 2012).

The application of satellite imagery to detect the presence of dust storms has been studied extensively in the past twenty years. A commonly-used satellite dust detection method named Reverse Absorption Technique (RAT) applies the Brightness Temperature Difference (BTD) at two or more wavelengths. The physical principle of RAT is that dust particles absorb more infrared radiation at shorter wavelengths, while ice or liquid water particles exhibit higher absorption at longer wavelengths (Prata, 1989; Ackerman, 1997; Zhao et al., 2010). From Pavolonis et al. (2006), liquid water clouds, ice clouds and clear sky are generally characterized by a positive BTD between 11 μm and 12 μm channels, while the value is negative for non-opaque dust clouds in a dry atmosphere. Ellrod et al. (2003) developed an algorithm namely "Three band Volcanic

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Ash Product" (TVAP) for improving the detection of volcanic ash and dust storm, which utilizes BTD between three IR bands on the Geostationary Operational Environmental Satellite (GOES) centered near 3.9, 10.7 and 12.0 μm. Legrand et al. (2001) proposed the Infrared Difference Dust Index (IDDI) based on observing thermal radiation (11–12 μm) emitted by the same scene over the course of several days, where significant changes can be evaluated as the potential dust areas. IDDI has successfully been applied to identify dust storms over China (Hu et al., 2008) as well as in the southwest Asia (Kaskaoutis et al., in press). Zhao et al. (2010) proposed a multichannel imager (MCI) algorithm, which relies on a combination of visible spectral contrast and spatial variability tests to detect dust aerosols for both land and water.

With the development of Artificial Intelligence (AI) technologies, many studies have highlighted the merits and effectiveness of using a Neural Network (hereafter NN) in monitoring the earth's atmosphere and environment (Gardner and Dorling, 1998; Knutti et al., 2003). NNs have been applied in aerosol retrieval applications based on different satellite platforms, and achieved promising results. For examples, the Maximum Likelihood Classifier (MLC) with a Probabilistic Neural Network (PNN) for automatic dust storm detection using bands 20, 29, 31 and 32 of the MODerate resolution Imaging Spectroradiometer (MODIS) satellite images was developed by Rivas-Perea et al. (2010). A total of 31 dust storm events were tested and validated, and the accuracy of PNN and MLC was 84% and 67% respectively. Elossta et al. (2013) applied NNs to detect dust storms using MODIS data over northern Africa. Han and Sohn (2013) developed a NN model for Aerosol Optical Thickness (AOT) retrieval from the Atmospheric Infrared Sounder (AIRS); good agreements were found by comparing the NN-derived AOT with MODIS-derived AOT and Cloud Aerosol Lidar with Orthogonal Polarization (CALIOP) identified dust scenes.

Integrated environmental modelling (IEM) has been applied for addressing scientific challenges, such as monitoring the environmental change detection and forecasting environmental problems (Granell et al., 2013). IEM focuses on the issues of resource integration, model sharing and reusing, and decision making through model integration (Bulatewicz et al., 2013). It is particularly interesting to chain several interoperable models where such a chain can potentially resolve more issues than the individual models alone, and it can enable user to address more complex tasks in different contexts. Geller and Turner (2007) proposed the concept of "Model Web", which is a generic concept for increasing access to models and their outputs in order to facilitate model-model interaction, resulting in webs of interacting models, databases, and websites. Integrating models into more complex and tightly-coupled model systems has been studied for decades and have led to great progress in predictive capabilities (Akbar et al., 2013; Castronova and Goodall, 2013; Demir and Krajewski, 2013). In this study, an integrated NN model was developed based on the IEM architecture, by combining statistical learning techniques (e.g. NN) and physical models within geoscience modeling workflow. Three dust storms events (i.e., April 27–30, 2009, March 20–22, 2010 and April 26–28, 2012) were used as case studies to evaluate the performance of the system. This system can derive near-real time aerosol optical properties, e.g. aerosol optical thickness using geostationary satellite imagery, and they can be further used to infer the sources of major dust storms and transportations of dust aerosols, as well as understanding the interactions between aerosols and regional/local energy budget in Asia.

This paper is organized as follows: Section 1 introduces the background and objectives of the study. Section 2 describes the study area and data used. Some widely-used approaches for remote sensing dust storm detection are documented and analyzed in Section 3. Section 4 discusses the design of the proposed integrated NN models. The model validation and case study are introduced in Section 5, and conclusions and recommendations are summarized in Section 6.

2. Data used and study area

2.1. Study area

The study area covers most of the East Asia from 20°N to 55°N latitude and from 95°E to 135°E longitude, which includes the main source regions for Asian dusts: the Gobi and the Taklimakan deserts (Fig. 1) (Sun et al., 2001; Shao and Dong, 2006). Approximately 240 Tg of dusts are re-deposited in Chinese deserts each year (Zhang et al., 1997), and 140 Tg of dusts falls off during their transportations in China (Zhang et al., 1997). Climatologically, dust storms in east Asia are reported dominantly in winter-spring season, and the highest frequency is observed in April. Approximately one-third to one-half of yearly dust storms occurs in April (Natsagdorj et al., 2003; Zhou and Zhang, 2003). During dust peak season, the estimated dust loads reach up to 1.7×10^{3} kg km^{-2} (Shao and Dong, 2006). Tan et al. (2012) analyzed the transport pathways of dust storms from two stations (Sunitezuoqi (41.37°N, 102.37°E) and Guaizohu (43.87°N, 113.63°E)) of main dust resources. They have concluded that the pathways are normally transported from Inner Mongolia deserts via the Loess Plateau to the North China Plain, and then entered into the East and South China Sea.

2.2. AERONET observations

Sunphotometers are commonly used to derive AOT through observing the direct solar irradiance. The NASA Aerosol Robotic Network (AERONET) is a federated network of ground-based sunphotometers, which contains over 700 sites around the world (Holben et al., 1998; Holben et al., 2001). The sunphotometers measure spectral AOT in eight wavelengths (center wavelengths are 340, 380, 440, 500, 675, 870, 1020 and 1640 nm, respectively), and the data can be used for producing inversion retrievals including fine and coarse-mode AOT, size distribution, single scattering albedo (SSA), and refractive index (Dubovik and King, 2000; Dubovik et al., 2006). In this study, the cloud-screened level 1.5 data generated from the AERONET version 2 direct sun algorithm at two stations, Beijing (39°N, 116°E) and SACOL (35°N, 104°E), during three dust-storm events (i.e., April 27–30, 2009, March 20–22, 2010 and April 26–28, 2012), were used to validate the results from NN-based AOT retrieval algorithm.

2.3. MTSAT satellite imagery

The Multifunctional Transport Satellite (MTSAT) is a geostationary satellite launched and operated by the Japan Meteorological Agency (JMA). The MTSAT-2 (also known as Himawari 7) used in this study was launched in 2006 and is positioned at 145°E longitude. The satellite carries five-band imager (Japanese Advanced Meteorological Imager, JAMI) and an imaging telescope, providing imagery for the northern hemisphere in 30 min basis (Puschell et al., 2002). In contrast to low-earth orbiting satellites, geostationary satellites provide earth observation data with relatively higher temporal resolution. Hourly brightness temperature (hereafter BT) images derived from four infrared channels (mid-infrared: IR3 and IR4; thermal-infrared: IR1 and IR2) and one visible channel (VIS) were used in this study. The parameters of each channel are illustrated in Table 1.