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A physical knowledge-based machine learning method for near-real-time dust aerosol properties retrieval from the Himawari-8 satellite data

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Abstract

Monitoring dust aerosol properties is critical for the studies of radiative transfer budget, climate change, and air quality. Aerosol optical thickness (AOT) and effective radius (R_{eff}) are two main parameters describing the optical and microphysical properties of airborne dust aerosol. Satellite remote sensing provides an opportunity for estimating the two parameters in spatial coverage and continuously. To take the merits of machine learning algorithms and also utilize the physical knowledge discovered in the conventional retrieval algorithms, a physical-based machine learning method was proposed and applied on the Himawari-8 geostationary satellite for robust retrieval of dust aerosol properties. The main concepts of this study comprise i) constructing the model input data by extracting highly informative features from the Himawari observations according to physical knowledge and ii) exploiting the utility of six state-of-the-art machine learning algorithms in dust aerosol retrieval. The algorithms include artificial neural network (ANN), extreme boost gradient tree (XGBoost), extra tree (ET), random forest (RF), support vector regression (SVR), and kernel Ridge regression (Ridge). The ground-truth AOT and R_{eff} data from AERONET stations were supplied as output labels. The cross-validation technique was adopted for model training and the results show that the ANN model is superior to the other machine learning models for both AOT and R_{eff} estimation, which exhibits the lowest mean absolute error (MAE = 0.0292 and 0.0981) and the highest correlation coefficient (r = 0.98 and 0.84). When validated on an independent dataset, the ANN model achieved the lowest MAE (0.0334 and 0.1487), and the highest r (0.94 and 0.63). More importantly, when compared against representative physical-based algorithms, the developed ANN model still retains the best performance. Furthermore, the ANN model shows an overall better performance than other machine learning models and also the JAXA Himawari-8 Level-2 AOT product, with examples exhibited in three dust storm events and for continuous monitoring of one of the dust storm events. Additionally, feature importance analysis implies that the important features of dust aerosol identified by the ANN model are consistent with that in physical model-based algorithms. In summary, this study shows great potential for generating near-real-time products of dust aerosol properties from Himawari satellite data. These products can provide a scientific basis for climate and meteorological study regarding severe dust storms.

Keywords: natural dust aerosol; artificial neural network; XGBoost, third-generation geostationary satellite

1. Introduction

Dust storm is a global natural disaster mainly originating in arid and semi-arid regions covering areas from the Sahara Desert and the Middle East to the great Indian Desert and the mid-latitude deserts of Central Asia, China, and Mongolia (Akhtar et al., 2018). Mineral dust, mainly coming from dust storms, is one of the major atmospheric aerosols that constitutes the most considerable mass abundance compared with other aerosols (Griggs and Noguer, 2002). It has a wide range of environmental and climate impacts (Choobari et al., 2014; Tegen and Lacis, 1996) and can adversely affect human health (Aili and Oanh, 2015). East Asia is particularly influenced by active dust storm activities. For instance, in 2021, this region was struck by a series of dust storm activities throughout the spring (March to May), resulting in severe casualties and economic losses (https://en.wikipedia.org/wiki/2021_East_Asia_sandstorm, accessed on June 1st, 2022). Natural mineral dust originating from the Taklimakan and Gobi deserts in China and Mongolia can be transported to nearby populated areas (Li et al., 2020a) such as Beijing, Tianjin, Seoul, and Tokyo, leading to a remarkable degradation of the city environment. This necessitates studies to characterize the dust aerosol properties, thus providing scientific evidence to assist control strategies.

Aerosol properties are generally characterized by their optical and microphysical properties in terms of aerosol optical thickness (AOT) and effective radius (R_{eff}). AOT is a metric of the radiation reduction after the light passes through the distance of a column atmosphere(Grainger, 2012). R_{eff} is the area-weighted radius and is defined as the ratio of the size distribution volume to the projected area (Grainger, 2012). R_{eff} has been extensively employed to represent the particle size distribution since the optical properties are susceptible to this parameter (Grainger, 2012). Satellite remote sensing provides an effective way for aerosol properties retrievals due to their broad coverage and continuous observations.

Conventional retrieval algorithms are typically based on physical models, i.e., the radiative transfer model that can simulate the radiance at the top of the atmosphere (TOA). The aerosol properties are then retrieved by comparing the model simulated radiance stored in a precomputed Look-up Table with the satellite observed radiance (Kaufman et al., 1997b). Yet retrieving aerosol properties over the land surface is still a challenging task due to the difficulty of separating the contribution of the atmospheric aerosols from land signals received by satellite at the TOA (Lee et al., 2009). Conventional physical retrieval algorithms use either visible near-infrared (VIR) bands mainly for anthropogenic aerosols, or thermal infrared (TIR) bands mainly for dust aerosols. For VIR techniques, the success of retrieval greatly relies on the reflectance contrast between the surface and the TOA. Notably, the determination of surface reflectance constitutes the most critical part of the representative algorithms of aerosol retrieval nowadays. The Dark Target algorithm estimates the surface reflectance of the blue and red bands from the apparent reflectance of the near-infrared band (i.e., around 2.1 μm) over the dark areas (Kaufman et al., 1997b), while the Dark Target algorithm is not applicable over a bright surface. The Deep Blues algorithm was developed to overcome such limitations by adopting a blue band for retrieval because bright surfaces tend to have a relatively low reflectance at the blue band (Hsu et al., 2004). The first-generation Deep Blue algorithm uses a predefined static reflectance library at the blue band (Hsu et al., 2004) and the second-generation algorithm improves the surface reflectance estimation by accounting for the land cover type, normalized vegetation index, and scattering angle (Hsu et al., 2013; Hsu et al., 2017; Hsu et al., 2019). Additionally, the surface reflectance (i.e., the bidirectional reflectance parameters) can also be simultaneously retrieved with aerosol information using the time series of MODIS measurements as demonstrated by the Multi-angle Implementation of Atmospheric Correction (MAIAC) algorithm (Lyapustin et al., 2011). The Minimum Reflectance Technique (MRT) has also been widely used to derive the surface reflectance which was initially utilized by Wong et al. (2011) for aerosol retrieval, specifically over bright surfaces, such as urban areas. Choi et al. (2018) applied the MRT on geostationary satellites. Yoshida et al. (2018) advance this algorithm by constructing the second minimum reflectance within a period to eliminate the cloud or topology shadow effect. Apart from considering the surface reflectance during the retrieval process, von Hoyningen-Huene et al. (2003) initiated the Bremen Aerosol Retrieval (BAER) algorithm, which excludes the influence of surface and molecular reflectance by subtracting them from the TOA reflectance and only leaves the aerosol reflectance in the AOT retrieval process. The BAER was then advanced and adapted to aerosol retrievals in northeast Asia in a series of follow-up works by focusing on the refinement of aerosol models and the surface reflectance calculation (Lee et al., 2007; Lee and Kim, 2010; Lee et al., 2004). The above algorithms normally incorporate the look-up table technique in retrieval to save computation time. Rather, Bilal et al. (2013) developed a simplified aerosol retrieval algorithm, which does not require precomputed look-up table and it retrieves AOT by directly using the local urban aerosol properties and the surface reflectance from MODIS product with a simplified radiative transfer equation. By far, these algorithms have achieved great success for anthropogenic aerosol retrievals, yet they may exhibit restricted applicability for dust aerosol retrieval.

VIR techniques may not work well when the aerosol signal is hard to separate from the land surface, which is likely to occur over the desert surface where the dust aerosol reflectance is very similar to that of the desert surface, and thus lead to a diminishment of reflectance contrast. Instead, the TIR channels are more suitable under such situation, which is preferentially used for dust aerosol retrieval while not for anthropogenic aerosols because TIR spectra are sensitive to coarse particles (size > 1 μm) but transparent to fine particles (< 1 μm). Early studies have verified the capabilities of TIR data for quantitatively retrieving dust properties through rigorous theoretical simulation and analysis (Ackerman, 1989, 1997; Legrand et al., 1989;

Legrand et al., 1988; Shenk and Curran, 1974; Wald et al., 1998). These methods can be mainly classified into two categories: the thermal contrast of a single band and the brightness temperature difference of two bands. Firstly, the appearance of dust aerosol can cause substantial degradation of the brightness temperature received at the TOA due to that the adiabatic lapse rate suggests a temperature decrease of lifted airborne dust compared to the surface; additionally, airborne dust can block the solar energy reaching the surface, thus further decreasing the brightness temperature received at TOA (Legrand et al., 1989; William and Robert, 1974). Secondly, the brightness temperature difference, i.e., the BTD_{11-12}, $BTD_{8.6-11}$, and $BTD_{3.7-11}$ were also demonstrated to have the potential of inferring dust AOT based on the fact that silicon has an inverse absorption at the wavelength around 11 μm (Ackerman, 1989, 1997; Wald et al., 1998). Especially, the $BTD_{8.6-11}$ is found to be sensitive to dust particle size (Wald et al., 1998). In subsequent studies, these two methods have been widely used for dust aerosol retrievals. The BT_{11} and BTD_{11-12} have been used for simultaneous retrieval of particle sizes, AOT, and total masses, with the observation data obtained from the MODIS, SEVIRI, and MTSAT (Gu et al., 2003). Eight thermal channels from the hyperspectral sensor of AIRS have been employed to simultaneously estimate the dust layer height and AOT (DeSouza - Machado et al., 2010; Peyridieu et al., 2010; Pierangelo et al., 2004; Yao et al., 2012). Additionally, the 9.32-μm channel (of the AIRS sensor) that is sensitive to dust particle size was further used to estimate the R_{eff} (Peyridieu et al., 2012; Pierangelo, 2005).

In the conventional physical algorithms, tackling the radiative transfer model is always an ill-posed problem because unknown parameters (surface states, atmosphere states, aerosol chemical component, AOT, R_{eff}, et al.) are more than knowns (satellite observations). Thus, in addition to the surface reflectance or temperature, the other unknowns should also be predetermined to retrieve the AOT and R_{eff}. Moreover, the physical algorithms use either VIR or TIR information, and relatively little work has been attempted to integrate these techniques for dust aerosol retrieval. Notably, the machine learning method inherently allows for the integration of multiple data sources, which is data-driven and does not involve prerequisites. The artificial neural network (ANN) or more specifically, the multilayer perception neural network (MLP-NN) has been extensively employed to facilitate dust aerosol retrievals. Lee and Sohn (2012) retrieved nighttime dust AOT from MODIS infrared measurements. Han and Sohn (2013) retrieved both AOT and dust height from a hyperspectral sensor (i.e., AIRS) with 234 infrared channels. Xiao et al. (2015) retrieved dust AOT from observations of a geostationary satellite of MTSAT. For dust size retrieval, Taylor et al. (2014) demonstrated retrieving aerosol size distribution with a neural network algorithm from satellite products. Although it offers great potential for retrieving size parameters using machine learning methods, the incorporation of the MODIS and TOMS Level-2 AOT products as inputs may lead to the accumulation of retrieval uncertainties inherited in the machine learning models. Also, Xiao et al. (2015) collected output data from MODIS Deep Blue AOT product, which may have lower accuracy compared with the ground-truth AERONET AOT and thus is not recommended. Current machine learning methods for dust aerosol retrieval demonstrate limited abilities mainly because they use relatively limited information, i.e., the spectral information at the thermal spectrum. The temporal information and the visible infrared information have not been fully utilized. Besides, some state-of-the-art regression machine learning algorithms extensively used in other remote sensing domains have been rarely exploited for dust aerosol retrieval.

As the newly third-generation geostationary satellite, the Himawari-8 started operating on July 7, 2015. Unlike previous geostationary satellites, it carries a new sensor called the advanced Himawari imager (AHI) that offers improved spectral, spatial, and temporal resolutions (Bessho et al., 2016; Daisaku, 2016). The other third-generation geostationary satellites carry similar advanced sensors as the AHI. With considerably more information measured, these satellites are expected to provide great opportunities for global hazards monitoring, e.g., dust storms. Given the fine temporal resolution of Himawari-8 observations, the surface reflectance and temperature can be well characterized by taking the clear-day pixels over a certain period (Lim et al., 2018; Zhang et al., 2006). Such that the reflectance/brightness temperature contrast caused by dust aerosol can be extracted by subtracting the reflectance/brightness temperature at the surface from the counterparts at the TOA, in a manner similar to the construction of Infrared Difference Dust Index (Legrand et al., 2001). Besides, the Himawari-8 observations can be used to construct most of the dust indices that developed in our previous studies (Li et al., 2020a). Overall, this satellite supplies abundant information for dust aerosol retrieval.

The primary objectives of this study are to 1) develop a physical-based machine learning model for near-real-time dust aerosol retrieval by employing input features exclusively from AHI data (or at most from ancillary static products); 2) exploit the utility of six state-of-the-art regression machine learning algorithms (i.e., ANN, XGBoost, ET, RF, SVR, and Ridge) for AOT and R_{eff} retrieval of dust aerosol. This paper is structured as follows: section 2 firstly introduces the research area and materials used briefly and then describes the details of the machine learning method and its integration with physical knowledge. The results of model evaluation and application are then presented in section 3. Section 4 then discusses the results, and section 5 provides a conclusion.

2. Materials and methods

2.1. Study area

The study area covers northeast Asia ranging between 30-50°N, and 100-142°E (Fig. 1), located downwind of the second-largest deserts (Taklimakan and Gobi deserts) and covers the four megacities of Beijing, Seoul, Pyongyang, and Tokyo. Due to cyclonic depressions over Mongolia and cold frontal systems (Sun et al., 2001), dust storms frequently occur over this area, especially in the spring season. Worse still, the topography decreases from west to east, making this area an excellent pathway for dust transportation. Nine AERONET sites located along the dust-storm pathway in this area were selected to obtain long-term ground-truth data.

Fig. 1

2.2. Data

Satellite measurements and digital surface elevation data were collocated with ground data to construct the training dataset. The Himawari-8 satellite carrying the Advanced Himawari Imager (AHI) was launched in October 2014 and started operating in July 2015 from a geostationary orbit over the equator at ~140°E. It leads the third-generation geostationary orbiting satellites (GEOs), followed by GOES-R, Himawari-9, FY-4A, Geo-KOMPSAT-2A, GOES-S, MTG-I1, and FY-4B (Miller et al., 2016), which are equipped with similar advanced optical sensors with AHI. Compared with the previous GEOs, Himawari-8 offers significantly improved spatial, spectral, and temporal resolution. AHI scans one third of the earth every 10 minutes (full disk) at 16 channels: 6 VIR (0.47, 0.51, 0.64, 0.86, 1.6, and 2.3 μm) and 10 TIR (3.9, 6.2, 6.9, 7.3, 8.6, 9.6, 10.4, 11.2, 12.4, and 13.3 μm) channels (Bessho et al., 2016). The first four VIR band images (0.5 km spatial resolution at the red band and 1 km resolution for others) are resampled to the lowest spatial resolution of 2 km as TIR bands. Besides, the JAXA Himawari-8 Level-2 AOT product (hereafter JAXA AOT) was used in this study for comparison (Yoshida et al., 2018). Both the observation data and AOT product were obtained from the Japan Aerospace Exploration (JAXA) Himawari Monitor P-Tree System (https://www.eorc.jaxa.jp/ptree/index.html, accessed on April 9, 2021).

Surface elevation can partly account for the topologically induced variations of the bidirectional reflectance distribution (Sandmeier and Itten, 1997). The digital elevation modeling (DEM) data representing the surface elevation is obtained from the Shuttle Radar Topology Mission by NASA and NGA at a 30 m spatial resolution (https://earthexplorer.usgs.gov/, accessed on April 9, 2021). The DEM was also resampled to 2 km spatial resolution.

The ground-truth AOT and R_{eff} were collected from the post-calibrated and cloud-screened Level 1.5 products (Version 3.0) offered by an international federated ground-based aerosol network, the AERONET (https://aeronet.gsfc.nasa.gov/, accessed on April 9, 2021). The sunphotometer directly measures the AOT according to the Beer-Lambert-Bouguer law with wavelength-independent absolute uncertainty at the level of ± 0.01, which is mainly caused by the solar channel calibration error (Dubovik and King, 2000; Holben et al., 1998). The aerosol size distribution, complex refractive index are simultaneously retrieved from all available spectral AOT measurements and angular sky radiances; these retrieved products exhibit varying accuracy for different aerosol types while providing sufficient accuracy for satellite validation (Dubovik and King, 2000; Sinyuk et al., 2020). Accordingly, the AERONET products are widely used as ground truth for satellite retrieval (Kim et al., 2014; Lee et al., 2005; Lim et al., 2018). The AERONET AOT at 550 nm was calculated from AOT values at 440 nm and an angstrom exponent (440-670 nm) based on the power law (Ångström, 1929). In this study, AOT and R_{eff} data at nine AERONET stations (Fig. 1) from 2015 to 2021 were collected to construct the training and test datasets.

In addition, given that AERONET provides spatially sparse-distributed ground-truth AOT data, the MAIAC AOT product retrieved from MODIS measurements was adopted for AOT retrieval comparison for dust storm events as it offers AOT product with a broad and continuous spatial coverage (Lyapustin et al., 2018). The MAIAC AOT has been extensively validated against ground-based observations in different regions, such as China (Zhang et al., 2019), South Asia (Mhawish et al., 2019), and South America (Martins et al., 2017), and it was demonstrated to agree well with ground-based AOT, i.e. 0.924 for Aqua and 0.933 for Terra (Zhang et al., 2019) and aligned well with AOT derived from Deep Blue and Dark Target retrieved AOT products (Liu et al., 2019b). Considering the high reliability and high spatial resolution (1 km) of MAIAC AOT, we thus incorporated the MAIAC AOT product for cross-validation. Notably, although the MAIAC AOT product is accurate and in high spatial resolution, its low temporal resolution (daily) limits real-time monitoring of atmospheric study, especially for dust storm activities. Our study provides a way for near-real-time estimation of dust aerosol properties. The MAIAC product was collected from the NASA EarthData center (https://search.earthdata.nasa.gov/search).

2.3. Method

2.3.1. Physical-based dust aerosol monitoring

The dust aerosol exhibits distinct spectral, temporal, and spatial features compared to the cloud and background surfaces (Li et al., 2020a). Eight typical dust storm indices that well characterize the spectral signatures of dust aerosol are constructed as the input features, which include four typical brightness temperature differences (BTD), the three-band volcanic ash product

(TVAP), normalized dust difference index (NDDI), D-parameter, and red-blue ratio. The BTD is the most widely used dust index in literature for both detection and retrieval of dust aerosol, which is based on inverse absorption at the wavelength around 11 μm. Meteorological clouds generally absorb radiation increasingly with longer wavelengths at the thermal spectrum, whilst dust aerosol absorbs more radiation at the wavelength of 11 than 12 μm, and thus it generates a unique negative BTD_{11-12} (Ackerman, 1989, 1997; Wald et al., 1998). The TVAP combines BTD_{11-12} and $BTD_{3.7-11}$, which is demonstrated to be sensitive to both dust presence and dust intensity (Ellrod et al., 2003). The NDDI is a typical dust index for distinguishing dust storms from meteorological clouds, utilizing VIR bands (Qu et al., 2006). D-parameter specifically separates dust aerosol from cirrus clouds, which combines both VIR and TIR wavelengths (Roskovensky and Liou, 2005). The red-blue Ratio (Ratio = r_{red}/r_{blue}) has been adopted to distinguish dust and non-dust aerosol (Kaufman et al., 1997a) and was demonstrated to be more sensitive to R_{eff} than AOT and mean dust layer altitude (Lee and Lee, 2015). In this study, a new index coined as the color index was developed which is demonstrated to highlight the yellow color of dust storms. The formulation of these spectral indices can be referred to in Table A2 in Appendix.

Additionally, the presence of dust aerosol can create substantial anomalies compared against the clear-sky background. The airborne dust aerosol can decrease the radiation at thermal bands. It can also increase the reflectance at blue bands compared to the densely vegetated surface background. The temporal features include the six VIR indices which denote the difference between observed and background reflectance at six VIR bands and are coined as difR; ten TIR indices representing the infrared dust difference index at ten TIR bands which are named IDDI. These temporal features reflect the magnitude of the dust aerosol signals. The background reflectance image at the blue band was constructed by taking the second-minimum reflectance (Yoshida et al., 2018), whereas the background temperature image at the wavelength of 11 μm was built by extracting the maximum brightness temperature (Legrand et al., 2001), both over the previous 15-day period. Background reflectance or brightness temperature images (designated as minR and maxBT) of the other VIR and TIR bands were anchored to the bands at blue and 11-μm, respectively. These background images were composited by taking the corresponding reflectance or brightness temperature on the same day with the blue or 11-μm band. The composited background images are used to approximate the surface reflectance and brightness temperature under the clear sky. Subsequently, the difR and IDDI were calculated by subtracting those background images from the corresponding AHI observed reflectance and brightness temperature at TOA. The spatial feature is represented by the standard deviation at the near-infrared band (signified as STD-R0.86) because dust normally displays a more homogeneous spatial distribution than cirrus at the near-infrared band.

The abovementioned physical knowledge was utilized to constrain the machine learning models by compiled as input features. In addition, the illumination geometries should also be included in the input features due to their significant impact on reflectance. Such geometries include the solar zenith angle (SOZ), satellite zenith angle (SAZ), satellite azimuthal angle (SAA), and relative azimuth (PHI) between the Sun and satellite (Kaufman et al., 1994). An overview of this study is presented in Fig. 2, which consists of three parts: data preparation, model training, and model application.

Fig. 2

2.3.2. Training and test dataset construction

The data set was established by spatially and temporally collocating AHI and DEM data with ground-truth AERONET data. Firstly, the external DEM data were resampled to 2 km to keep the consistency with the spatial resolution and location of AHI pixels. Then, the AHI and DEM grid pixels were collocated with the corresponding ground AERONET stations by finding the closest pixels to the stations according to the geolocation (longitude and latitude). In this way, AERONET stations are matched with the AHI observations spatially. Additionally, the temporal coincidence was matched by retrieving the AHI observations within five minutes of the corresponding AERONET measurements. Consequently, the AERONET data collected from the nine AERONET stations spanning five years from August 2015 to December 2020 were matched with AHI and DEM data, producing 34,793 samples.

For each training sample, its input features were compiled as a vector composed of AHI observations, composited spectral dust indices, temporal dust indices, satellite illumination geometries, and surface altitude. Consequently, a vector with 47 dimensions was built, which is expressed as X_i = [R_i, BT_i, dust indices, difR_i, IDDI$_i$, geometries, DEM]. The output data (i.e., the AOT and R_{eff}) are collected from AERONET products. The machine learning models for AOT and R_{eff} estimation are trained individually, whereas the input features for training the AOT models and R_{eff} models are consistent. It is anticipated that the machine learning models can automatically identify the respective sensitive features (the important features) corresponding to the AOT and R_{eff}.

Cloud masking was implemented to remove the remaining cloudy cases for quality control. A sample satisfying any of the following conditions was masked as being cloud contaminated and discarded: 1) $R_{0.64} > 0.30$ & $R_{0.51} > 0.28$ & $R_{0.47} > 0.26$; 2) $BT_{11} < 260$; 3) $R_{0.47} > 0.2$ & $R_{0.64} / R_{0.47} < 0.95$. A total of 23,700 records were maintained after cloud masking. Then, a relaxed dust aerosol sample selection (or dust storm detection) algorithm was further applied in order to eliminate the bias towards anthropogenic aerosol and thus balance the data because anthropogenic aerosols account for a large portion of the original samples. The dust aerosol selection algorithm is defined as TVAP > 100 & $BTD_{11\_10} > 0.2$ & $R_{0.47} < 0.3$. As a result, 2,511 training (from the year 2015 to 2019) and 697 (in the year 2020) test samples were obtained. Noticeably, only 10 percent of the samples were maintained after dust aerosol selection. The small amount of dust aerosol cases implies that AERONET stations record limited dust cases. Subsequently, all inputs were normalized by calculating the Z-values for scale consistency.

2.3.3. Model establishment

The machine learning algorithm is an entirely data-driven approach that can learn the relationship between input features (e.g., satellite measurements) and output target (e.g., AOT and R_{eff}) by approximating a flexible model directly from data. Six machine learning algorithms extensively used in quantitative remote sensing are investigated, namely the neuron-based ANN, the tree-based XGBoost, ET and RF, and the kernel-based SVR and Ridge algorithms. In addition, the model performance could be fine tuned with the respective hyperparameters.

ANN has been considered in many applications for developing nonparametric and nonlinear regression. Hornik et al. (1989) argued that in a compact input space, the neural networks are perceived as universal approximators, and a two-layer network with linear outputs is proved to be capable of approximating any continuous function to arbitrary accuracy when given sufficient hidden units in the network (Hornik et al., 1989). The network architecture, i.e., the number of layers, neurons per layer, activation function, learning strategy (i.e., cost function), and optimization strategy, are required to be predefined in ANN.

The RF, ET, and XGBoost are all ensemble methods of the decision tree algorithm. The decision tree learns from one pathway of decisions and hence can be easily overfitted. The differences among the three algorithms mainly lie in that RF and ET adopt the bagging ensemble technique, whereas XGBoost employs the boosting ensemble technique. The RF and ET could improve the weak decision tree models by averaging several decision tree outputs, thereby reducing the variance; the XGBoost is based on the gradient boosting framework (Friedman, 2001) and further improves the gradient boosting algorithm by adding an extra regularization term into cost function and allowing for parallel processing to control overfitting and model complexity (Chen and Guestrin, 2016). Additionally, the RF differs from ET in selecting the training dataset and split method: the RF uses a bootstrap technique to determine split features based on a deterministic approach (or best split); in contrast, the ET uses all available data in the training dataset and randomly splits features (Geurts et al., 2006). Two main hyperparameters need to be defined for both ET and RF, which include the maximum depth and the number of estimators.

For XGBoost, additional hyperparameters including boosting parameters (i.e., booster and learning rate) and regularization parameters (i.e., L1 and L2 regularization term) also need to be determined.

The SVR can provide a unique global hyperplane. Unlike neuron-based algorithms, SVR is a discriminant regression technique that can analytically solve the optimization problem (Awad and Khanna, 2015). Its computational complexity is determined by the selected support vectors rather than the dimensionality of the input space, and thus the trained data should be representative of the overall population. Otherwise, the hyperplane can be prone to poor generalization (Awad and Khanna, 2015). Four main hyperparameters are tuned to achieve optimal performance, namely epsilon (the thickness of a tube), C (a penalty factor), kernel function, and gamma.

The ridge regression was originally the linear least square regression with the L2-norm regularization technique which is designed to minimize the effects of the correlations in input features (Hoerl and Kennard, 1970), while it is only applicable for solving linear regression problems. The kernel Ridge then introduces the kernel trick to achieve nonlinear regression by mapping the input features with a nonlinear kernel (Witten et al., 2017). It is generally employed to handle multi-collinearity problems and has been used in parameter retrieval from remote sensing data (Caicedo et al., 2014; Verrelst et al., 2012). Two main hyperparameters need to be defined: the parameter (alpha) controlling regularization strength and the kernel function.

All machine learning models were trained using the python programming language in the Spyder Integrated Development Environment. Three main python packages were imported for model training, which include Scikit-learn, XGBoost, and Keras. The Scikit-learn package was used to train the SVR, Ridge, RF, and ET models; the XGBoost and Keras were used to train the XGBoost models and ANN models respectively. All python packages are open source. Detailed information about the introduction and tuning procedure of the machine learning hyperparameter is given in Appendix A1.

2.4. Model performance evaluation

A cross-validation method was implemented in model performance evaluation to enhance the model's effectiveness by interchanging the training and validation set during the training phase. Five-fold cross-validation was adopted to train the models. The training set was first partitioned into five groups of approximately equal size. Five models were then trained iteratively using four of the five groups as training data and the remaining group as validation data in each run. The final prediction was the average of the five trials. Four metrics were used to evaluate the model performance during cross-validation, which includes the mean absolute error (MAE), mean absolute percentage error (MAPE), coefficient of determination (r^2), correlation coefficient (r), and expected error (EE). These metrics were formulated and explained in the

"Metrics" row of Table A2 in Appendix. For each machine learning algorithm, the MAE, MAPE, r^2, and r are collectively used to examine and identify the optimal models. Such optimal models were then evaluated for the generalization ability by testing them on an independent set.

3. Results

3.1. Cross-validation

In cross-validation, the ANN model is superior to the other machine learning models in both AOT and R_{eff} estimation. The cross-validation results are shown in Fig. 3 and Fig. 4 for AOT and R_{eff} models, respectively. The ANN model has the lowest MAPE (21.50%), MAE (0.0292), while the highest r^2 (0.97) and r (0.98) values. The three tree-based ensemble models, the XGBoost, ET, and RF show comparable performance with each other; they exhibit similar metric values with MAPE from 0.90 to 0.92, MAE ranging from 0.0405 to 0.0482, r^2 from 0.90 to 0.92, and r from 0.95 to 0.96. The SVR model shows superior MAPE (25.13%) and MAE (0.0350) values than the tree-based models, while it does not show higher r^2 (0.90) and r (0.95) values. The low r^2 and r values can be caused by the three noticeable outlier points in Fig. 3(f) with ground-truth AOT values greater than two. A similar situation can be noticed for the Ridge model in Fig. 3g, wherein three outliers are also with an AOT value greater than two. In Fig. 3c, d, and e, it can also be noticed that the former mentioned three points also depart from the 1:1 line, but with a small magnitude. This implies that both the tree-based and the kernel-based models have insufficient abilities for AOT and R_{eff} estimations under heavy dust aerosol conditions, of which the tree-based models reveal a relatively better performance than the kernel-based ones. Notably, the ANN model can still produce accurate AOT estimations under heavy dust aerosol conditions. Overall, for AOT estimation, the ANN model shows decent performance under both light and heavy aerosol situations; the tree-based models display favorable performance under light aerosol situations while inferior performance under heavy situations; kernel-based models can only provide satisfying estimations of AOT under light aerosol situations.

Fig.4 displays the cross-validation results for R_{eff} models. The ANN outperforms the other machine learning models with the lowest MAPE (18.95%), MAE (0.0981), and highest r^2 (0.70) and r (0.84). XGBoost, ET, SVR and Ridge show comparable performance with similar MAPE (24.95% to 28.22%), MAE (0.1264 to 0.1352), r^2 (0.49 to 0.54) and r (0.70 to 0.74). The RF shows the poorest performance which gives the highest MAPE (31.49%), MAE (0.1474), and lowest r^2 (0.42) and r (0.67). Overall, all models tend to underestimate the R_{eff} values. Meanwhile, it is found that model performance on R_{eff} estimation is much inferior to that on AOT estimation. This can be conceived from an understanding of the underlying physical theory: R_{eff} is a microphysical parameter that determines the single-scattering properties (Tanré et al., 1996), while AOT is an optical parameter that describes the column atmosphere and thus it is directly related with the radiances received by satellite sensors (Kaufman et al., 1997b). Specifically, the function relating the top of the atmosphere (TOA) radiance and the AOT can be given by a radiative transfer model (Kaufman et al., 1997b), while the function that associates TOA radiance and R_{eff} is formed by coupling the single scattering model and radiative transfer model (Tanré et al., 1996), which is more complex.

Fig. 3

Fig. 4

3.2. Test on an independent dataset

The models were also tested on an independent dataset collected in the year 2020, which has not been used in training. Fig. 5 and Fig. 6 show the scatterplots of the model-estimated AOT and ground-truth AOT provided by AERONET. The results reveal that ANN retains the best performance on both AOT and R_{eff} estimation. For AOT estimation, the ANN model gives the lowest MAPE (31.77%) and MAE (0.0334) values, while the highest r^2 (0.88), r (0.94), and within EE (93.4%) values. The other machine learning models present comparable performance with each other exhibiting MAPE ranging from 41.80 to 52.92%, MAE from 0.0415 to 0.0535, r^2 from 0.65 to 0.8, r from 0.82 to 0.91, and EE from 85.2% to 88.5% (Fig. 5).

For R_{eff} estimation, all machine learning models manifest a substantial decrease in performance on the independent test set compared with that in cross-validation. The ANN model shows the largest performance reduction and the performance discrepancies between the ANN model with the other models were narrowed down. Nevertheless, the ANN model is still superior to other machine learning models with the lowest MAE, MAPE, and highest r^2, r, and EE (Fig. 6). All the metrics of the machine learning model performance on both cross-validation and independent test set are summarized in Tables A4 and A5.

Fig. 5

Fig. 6

3.3. Application to three spatially diversified dust storm events

The machine learning models were applied to three dust storm cases that occurred in the year 2017 (May 3 and 4), 2019 (May 15) which are abbreviated as DS20170503, DS20170504, DS20190515. The three dust storm cases were selected mainly due to 1) they exerted influences over a noticeable region and population and 2) they represent the most frequent transport pathways for dust storm activities in northeast Asia. Notably, although the dust storms over the Taklimakan desert occurr frequently throughout the year, most of which are within this area and do not travel downwind, and thus a very limited population is affected by them. Therefore, dust storms over the Taklimakan deserts were not considered. The selected three dust storm cases all originated from the Gobi areas in Mongolia and Inner Mongolia of China. The results of the three dust storm cases are depicted in Fig. 7, 8, and 9. In these figures, the subplots (a) to (c) display the true color, false color, and MAIAC aerosol type images. The true color images were composed of $R_{0.64}$, (1-0.07)*$R_{0.51}$+0.07*$R_{0.86}$ and $R_{0.47}$ as the respective red, green, and blue channels proposed as that in (Miller et al., 2016), in which a hybrid green band that combines the original blue and near-infrared bands is found to boost the signal over green vegetation and barren desert surfaces. The false-color images were composited by $BTD_{12\text{-}11}$, $BTD_{8\_11,}$ and $BT_{10.8}$ as the respective red, green, and blue channels (Martínez et al., 2009), by which dust storms can be highlighted in magenta. These images can provide a rough visual interpretation of dust storm distribution. The subplots (d) to (f) show the AOT images retrieved by the ANN model, MAIAC algorithm, and JAXA algorithm. The subplots (g) to (i) illustrate the ANN model estimated R_{eff}, $BTD_{12\text{-}11}$, and BTD_{8_11} images. The two BTD images are displayed here for a qualitative verification of R_{eff} estimation as conventional physical-based studies found that effective radius exerts a distinguished effect on the $BTD_{12\text{-}11}$ (Zhang et al., 2006) and BTD_{8_11} (AlBadi et al., 2018). The subplots (j) and (k) show the scatterplots of the comparison between ANN-estimated AOT (ANN_AOT) and the JAXA AHI AOT (AHI_ AOT) product against the MAIAC-retrieved AOT (MCD_AOT).

Notably, we aim to exploit the machine learning model's ability in properties retrieval, especially for dust aerosol and thus pixels to be retrieved need to be identified as dust aerosol in high confidence. Accordingly, a conservative dust storm detection algorithm was applied, which means that pixels identified by this algorithm are dust pixels in high confidence, while part of pixels with thin dust aerosol layer may be ignored. The conservative dust storm detection algorithm is defined as (1) $BTD_{12\text{-}11} > 0.5$ & $IDDI_{11} > 5$ & $difR_{0.47} > 0.02$) or (2) D_pameter > 3 & Color index > 0 & $IDDI_{11} > 5$ & $difR_{0.47} > 0.02$. Note that dust storm detection is applied after the cloud masking algorithm (see Section 2.3.2). Visual comparisons between subplots (a) to (c) in Fig.7, Fig.8, and Fig.9 evidenced that such a conservative dust detection algorithm can well capture the heavy dust aerosol areas. The ANN_AOT are more consistent with the MCD_ AOT than AHI_OP_AOT images. Notably, the AHI_AOD product exhibits insufficient spatial coverage for dust storm areas. Furthermore, quantitative comparisons between ANN_AOT and AHI_OP_AOT against MCD_AOT (Fig. 7j and Fig. 7k) suggest that ANN_AOT is more consistent with MCD_AOT than AHI_AOT. Also, the same results are found for the DS20170504 (Fig.8) and DS20190515 (Fig.9).

The above analysis implies that the ANN algorithm is superior to the current operational AHI algorithm in dust AOT retrieval over the study region. The AOT images of the DS20170503, DS20170504, and DS20190515, predicted by the other machine learning, and their comparisons against the MCD_AOT were illustrated in Fig. A2, A3, and A4. Results reveal that the other machine learning models only have certain abilities on estimating the dust AOT of DS20170504 (Fig. A3) but may not work in the estimation of DS20170503 and DS20190515 (Fig. A2 and A4). The satisfactory results on DS20170504 can be attributed to the fact that the affected area of this dust storm is very close to or overlaps with the AERONET stations used for training thus, similar situations being learned during the training. Whereas the DS20170503 and DS20190515 covered areas are far from the AERONET stations and possibly, the situations are rarely seen during the training. The above analysis implies that ANN demonstrates a much higher generalization ability. Specifically, the ANN model can estimate the dust AOT accurately not only over the anthropogenic dominated or largely affected areas (e.g., the Capital Economic Zone of China), but also over dust dominated areas (e.g., Mongolia) or under heavy dust aerosol situations.

Fig. 7

Fig. 8

Fig. 9

3.4. Application to a temporally continuous dust storm event

Continuous monitoring of a dust event was performed to evaluate the performance of the ANN models under various illumination geometries (Fig. 10). The formation, expansion, and transportation of the dust storm are well captured by the Himawari-8 satellite. Fig. 10 displays the true-color, ANN_AOT, and AHI_AOT images from UTC 2:00 to 7:00 on May 3 and 4, 2017. As revealed by the ANN_AOT images, on May 3, the magnitude of dust AOT increased from ~1.0 to ~3.0 with the formation and diffusion of the dust storms; on May 4, the magnitude of dust AOT decreased from ~3.0 to ~1.5 as the dust storm transports to and diffuses or deposits over the Bohai Sea. Whereas the AHI_OP_AOT images exhibit insufficient dust aerosol retrieval, which is sparse and discontinuous, and also they show much higher AOT values than the ANN_AOT images.

Fig. 11 presents the AOT values of this dust storm measured by the AERONET stations (Beijing, Beijing-CAMS, Beijing_PKU, and Beijing_RADI). It is found that ANN estimated AOT agrees quite well with AERONET AOT, both decreasing from ~2.8 to ~1.5 and finally reaching ~2.0 at UTC 8:00 (Fig. 11d). The operational AHI algorithm tends to underestimate the AOT with values less than 0.5 throughout the whole daytime over the areas covering these stations(Fig.

11c). The temporal images verify that ANN can give reliable dust AOT under various illuminations and is superior to the operational AHI AOT retrieval algorithm.

Fig. 10

Fig. 11

Fig. 12 depicts the temporal variations of the estimated R_{eff} ranging from UTC 2:00 to 7:00 on May 3 and 4, 2017. The upper panel in Fig. 12 shows the evolution and transportation process of the dust storm event. In the formation and expansion phase (May 3), the R_{eff} becomes large as more coarse dust particles are lifted into the atmosphere, generally from 1.5 to 2.2 μm on average (Fig. 12). Meanwhile, the core of the dust storm shows the value of R_{eff} up to 4 μm. In the transportation and deposition period (May 4), the R_{eff} decreases from 1.8 to 1.3 due to the deposition of coarse particles (Fig. 12). Fig. 13 displays a quantitative comparison between the ANN estimated and the AERONET retrieved R_{eff} of this dust storm over five AERONET stations. Although the R_{eff} values between UTC 2:00 to 7:00 are not available in AERONET, the general trends between the ANN estimated and AERONET R_{eff} are consistent (Fig. 13b).

Fig. 12

Fig. 13

4. Discussion

4.1. Comparison of the six machine learning models

Six machine learning algorithms, including the ANN, XGBoost, extra tree, random forest, support vector machine, and Ridge, have been comprehensively investigated for their utility in dust aerosol retrieval. These algorithms have been extensively utilized in satellite remote sensing, such as $PM_{2.5}$ estimation (Wei et al., 2021; Zamani Joharestani et al., 2019), PM_1 estimation (Li et al., 2020b), water chlorophyll estimation (Singhal et al., 2019), snow depth retrieval (Xiao et al., 2018). The ANN algorithm is the one that has been mostly adopted for aerosol properties estimation (Chen et al., 2020; Di Noia et al., 2015; Lanzaco et al., 2017; Mauceri et al., 2019). Generally, the six algorithms can be categorized into three types: neuron-based, tree-based, and kernel-based (Wu and Fan, 2019). Overall, the neuron-based ANN model shows the best performance among the six machine learning algorithms in cross-validation and on the independent test. When applied to dust storm events, the ANN model can not only well characterize the spatial variations but also capture the temporal trends of both the AOT and R_{eff} of the dust storms. However, the other machine learning models may not work well in estimating the dust storm events. It is inferred that the remarkable discrepancies in the performance of dust storm estimations mainly lies in the extrapolation ability of these machine learning algorithms. Normally, machine learning algorithms are deployed for "interpolating" data but have limited potential for "extrapolating" predictions that are far from their initial training set (Liu et al., 2019a). Nevertheless, some algorithms may show certain capabilities for extrapolating predictions that are near the initial training space. The neuron-based algorithm is proved to be capable of approximating any continuous function to arbitrary precision with sufficient hidden neurons (Hornik et al., 1989), implying that it has the potential to extrapolate beyond the training space (Pektas and Cigizoglu, 2017). Additionally, the kernel-based algorithms, i.e., the SVR and Ridge, have been demonstrated to show certain extrapolation abilities in previous studies (Crone et al., 2006), but perform poorly in our study. The tree-based algorithm, especially the XGBoost is a very powerful and efficient tool for regression (Chen et al., 2019), yet they have a critical shortcoming: incapable of extrapolation. Predictions made by tree-based algorithms are only based on a sum of values attached to tree leaves, which means that these algorithms can only make a good prediction for situations previously encountered in the training phase and cannot capture trends (Xu et al., 2005). This study gives a preliminary empirical demonstration of the extrapolation ability of the six machine learning algorithms. In-depth diagnostics of the extrapolation ability of these machine learning algorithms can be performed with an analytical model (i.e., a radiative transfer model), similar to (Martius and Lampert, 2016).

4.2. Comparison against previous studies

The satellite retrieved AOT results are generally validated with the AERONET AOT product in order to test how much it agrees with the ground-truth data by evaluating with a series of metrics, i.e., MAE, RMSE, *r,* and EE, as done in this study. Based on these metrics, a rough comparison was also carried out between the ANN model developed in this study with models developed in previous studies that employ either machine learning or physical-based algorithms. The metric comparison results are tabulated in Table 1. The developed ANN model for AOT estimation has a higher *r* (0.94) than that developed by Xiao et al. (2015) which gives *r* near 0.89 over a test set of 54 samples. The developed ANN model for R_{eff} estimation (r = 0.63) also shows advancement to the one developed by Taylor et al. (2014) that gives *r* less than 0.514. The developed ANN model was also compared with several physical model-based algorithms, including those specifically designed for AHI aerosol retrieval, i.e., the HiPARA algorithm developed by Su et al. (2021) and the algorithm developed by She et al. (2018) and the global AOT products, i.e., MODIS MAIAC AOT (Zhang et al., 2019), MODIS Dart Target, Deep Blue, and VIIRS AERDB product (Su et al., 2021). Notably, the HiPARA has already achieved high accuracy with MAE, RMSE, *r,* and EE equal to 0.082, 0.113, 0.939, and 82.5% compared against ground-truth AOT tested over 661 samples. The ANN model developed in this study shows even better metric values with lower MAE (0.0334), RMSE (0.0574), and higher *r* (0.940) and EE (93.4%) when tested over 697 samples. However, it should be noted that the comparison is not delicate enough because our model and the other models were not tested on exactly the same study areas and samples. The HiPARA, DT, DB, AERDB derived AOT in Su et al. (2021) and MAIAC AOT in Zhang et al. (2019) was validated against ground-truth AOT in a broader geospatial range (80–135°E and 4–53°N, and 72-132°E and 20-54°N, respectively) than our study area (30-50°N,100-142°E). As we mainly focus on dust storm frequently affected areas, we did not expand our study area to other parts (e.g., south part of China). Nevertheless, this comparison reveals that the ANN model has the potential to be comparable or even superior to physical models if trained with localized data in the interest of regions.

Table 1

4.3. The utility of physical knowledge in machine learning models

The physical knowledge of dust aerosol was embedded in the input features and a feature importance analysis was performed to examine the performance improvement resulting from the physical knowledge. Fig. A5 displays the results of the feature importance analysis estimated by the tree-based XGBoost, ET, and RF models using the impurity measure technique (Xia et al., 2008). Note that only the 10 most and 10 least important features are displayed in Fig. A5. It is found that the feature importance values of $difR_{0.47}$, $difR_{0.51}$, $difR_{0.64,}$ and DEM are significantly larger than the other features and the four features collectively constitute 73.6%, 59.3%, and 45.0% of the contribution among the 47 features to the respective XGBoost, ET and RF models in AOT estimation. Whereas, in R_{eff} estimation, the $BTD_{8\text{-}11}$, $BTD_{11\text{-}10}$, SAA, and SAZ outperform the other features and the four features collectively constitute the 59.7%, 25.8%, and 16.5% contribution to the respective XGBoost, ET, and RF models. These characteristics agree with physical knowledge: AOT is related with the reflectance contrast (i.e., difR) (Tao et al., 2017) and R_{eff} is associated with the $BTD_{8\text{-}11}$ (AlBadi et al., 2018). Fig. A6 displays the results of features importance analysis estimated by the neuron-based ANN model using a permutation importance method (Altmann et al., 2010) and all 47 features are displayed. Fig. A6(a) and (c) show that the respective ANN model for AOT and R_{eff} estimation exhibit similar patterns: the most important features are the temporal features characterizing the TIR contrast and VIR contrast and follow with the spectral features representing the brightness temperature differences. These composited temporal and spectral features exhibit comparable importance. In contrast, the original observations and DEM contribute relatively less. The above analysis indicate that the ANN model seems to identify most physical knowledge (i.e., the temporal and spectral features). Notably, the substantial discrepancies between the tree-based and ANN models may partly explain the performance difference between them due to that the tree-based models lay much emphasis on the several top features, while the ANN model accounts for the most temporal and spectral characteristics of dust aerosols. Overall, the above feature importance analysis implies the advancement of introducing physical knowledge in machine learning modeling.

4.4. Limitations

Although the ANN model has achieved relatively high accuracy, several issues should be addressed. First, the ANN model tends to underestimate both AOT and R_{eff} values, particularly under the situations of extremely heavy aerosol events. This can be attributed to the biases towards small AOT and R_{eff} values in the training data. Notably, the sunphotometer is unable to monitor aerosol optical properties in the situation of serious dust storms, particularly at dust-source areas as the severe dust storms are likely to be identified as clouds and removed in Level 1.5 and 2.0 products (Du et al., 2008). This is because the large AOT variations caused by severe dust storms can be very similar to clouds and thus cannot pass the smoothness procedure in the cloud-screening quality control scheme (Shin et al., 2019; Smirnov et al., 2000). As such, AERONET hardly records the AOT and R_{eff} values of the severe dust storm cases. A solution for this is to incorporate the data generated from physical models (i.e., the radiative transfer models) and used as part of training data (Reichstein et al., 2019). Second, unlike the physical models that establish a general theory and can be applied globally, the machine learning models have an inherent drawback of data-dependent, therefore the trained machine learning models are limited to the training regions and empirical. Third, the training and application of the models in this study are exclusively over the land surface, yet it has not been evaluated over the ocean where the dust storms are also likely to appear. For instance, the dust storms from the Gobi in Mongolia and China can be transported to the Pacific Ocean (Guo et al., 2017). Therefore, it is expected to extend this model over oceans. Also, the AERONET does not provide ground-truth data over the ocean (Xu et al., 2015), whereas the physical-model generated data are in relatively high accuracy and thus can be used as output data for model training. This is because the reflectance of the ocean surface is much lower, and homogeneous than the land surface, which is more favorable for retrieval (King et al., 1999).

4.5. Further study

The ANN model is expected to generate near-real-time AOT and R_{eff} estimations which may not be applicable for some physical model-based algorithms wherein part of the prerequisites are obtained from other products, such as the NCEP reanalysis data (Zhang et al., 2006), the MODIS land surface reflectance product (Su et al., 2021). These external products may be unavailable in near-real-time. Whereas the input features used in this study can all be obtained instantly once the Himawari satellite observations are made because all the spectral, temporal, and spatial features are generated from AHI observations, and the external DEM data is relatively static. As such, the ANN model can provide near-real-time (10-min) and 2-km spatial resolution simultaneous estimations of AOT and R_{eff}.

The future study will consider expanding the ANN model over the ocean. Additionally, the ANN model can be transferred to other regions covered by the third-generation geostationary satellite as the sensors onboard the other third-generation satellites (e.g., the FY-4A, Geo-KOMPSAT-2A, MTG-I1 to I4, and GEOS-R) provide similar spectral, spatial, and temporal resolution with the AHI sensor. A global coverage formed by this geostationary constellation for the estimation of dust aerosol properties is expected.

5. Conclusion

Six machine learning algorithms integrating physical knowledge have been employed for simultaneous dust aerosol optical (AOT) and microphysical (R_{eff}) properties retrieval. When compared against the AERONET AOT/R_{eff}, the ANN model shows an overall superior performance to the XGBoost, extra tree, random forest, SVR, and Ridge models, which shows the lowest MAE (MAE=0.0334/0.1485) and MAPE (MAPE=31.77%/18.95%), while the highest r^2 (r^2=0.88/0.70) and r (r=0.94/0.63). Furthermore, in applications to three severe dust storm cases, the ANN AOT images are consistent with the counterpart of the MAIAC product in spatial variations. Continuous monitoring of a dust storm event further reveals that the ANN model can well capture the temporal variations of dust aerosol for both AOT and R_{eff} estimations. These applications manifest the advancement of the ANN model to the AHI operational algorithm. Notably, the feature importance analysis verifies that the integration of physical knowledge in the machine learning model shows a significant improvement in the model performance. Besides, the sensitive features to AOT and R_{eff} identified by the ANN model agree favorably with the physical understanding of the dust aerosol. Due to the stability, accuracy, and physical interpretability of the ANN model, it is promising to be a practical retrieval algorithm. Further research should be directed toward transferring the ANN model to the other third-generation geostationary satellites, such as the FY-4A, Geo-KOMPSAT-2A, MTG-I1 to I4, and GEOS-R. Such that global near-real-time monitoring of dust storm properties is achievable by synthesizing the observations of the constellation.

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Reference

Ackerman, S.A., 1989. Using the radiative temperature difference at 3.7 and 11 μm to tract dust outbreaks. Remote Sens. Environ. 27, 129-133. https://doi.org/10.1016/0034-4257(89)90012-6

Ackerman, S.A., 1997. Remote sensing aerosols using satellite infrared observations. J. Geophys. Res. 102, 17069-17079. https://doi.org/10.1029/96JD03066

Aili, A., N.T.K. Oanh, 2015. Effects of dust storm on public health in desert fringe area: case study of northeast edge of Taklimakan Desert, China. Atmos. Pollut. Res. 6, 805-814. https://doi.org/10.5094/APR.2015.089

Akhtar, S., K. Zahedi, T. Bonapace, 2018. Sand and dust storms in Asia and the Pacific: opportunities for regional cooperation and action. United Nations Economic and Social Commission for Asia and the Pacific. Bangkok.

AlBadi, H., J. Boland, D. Bruce, B. Wedding, 2018. Estimating effective dust particle size from satellite observations. Remote Sensing Applications: Society and Environment. 11, 186-197. https://doi.org/10.1016/j.rsase.2018.07.004

Altmann, A., L. Toloşi, O. Sander, T. Lengauer, 2010. Permutation importance: a corrected feature importance measure. Bioinformatics. 26, 1340-1347.

Ångström, A., 1929. On the Atmospheric Transmission of Sun Radiation and on Dust in the Air. Geografiska Annaler. 11, 156-166. https://doi.org/10.1080/20014422.1929.11880498

Awad, M., R. Khanna, 2015. Support vector regression. Efficient learning machines. Springer pp. 67-80.

Bessho, K., K. Date, M. Hayashi, A. Ikeda, T. Imai, H. Inoue, Y. Kumagai, T. Miyakawa, H. Murata, T. Ohno, 2016. An introduction to Himawari-8/9—Japan's new-generation geostationary meteorological satellites. Journal of the Meteorological Society of Japan. Ser. II. 94, 151-183. https://doi.org/10.2151/jmsj.2016-009

Bilal, M., J.E. Nichol, M.P. Bleiweiss, D. Dubois, 2013. A Simplified high resolution MODIS Aerosol Retrieval Algorithm (SARA) for use over mixed surfaces. Remote Sens. Environ. 136, 135-145. https://doi.org/10.1016/j.rse.2013.04.014

Caicedo, J.P.R., J. Verrelst, J. Muñoz-Marí, J. Moreno, G. Camps-Valls, 2014. Toward a semiautomatic machine learning retrieval of biophysical parameters. IEEE J. Sel. Top. Appl. 7, 1249-1259. https://doi.org/10.1109/JSTARS.2014.2298752

Chen, T., C. Guestrin, 2016. Xgboost: A scalable tree boosting system. In: Proceedings of Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pp. 785-794.

Chen, X., G. de Leeuw, A. Arola, S. Liu, Y. Liu, Z. Li, K. Zhang, 2020. Joint retrieval of the aerosol fine mode fraction and optical depth using MODIS spectral reflectance over northern and eastern China: Artificial neural network method. Remote Sens. Environ. 249, 112006. https://doi.org/10.1016/j.rse.2020.112006

Chen, Z.-Y., T.-H. Zhang, R. Zhang, Z.-M. Zhu, J. Yang, P.-Y. Chen, C.-Q. Ou, Y. Guo, 2019. Extreme gradient boosting model to estimate PM2.5 concentrations with missing-filled satellite data in China. Atmos. Environ. 202, 180-189. https://doi.org/https://doi.org/10.1016/j.atmosenv.2019.01.027

Choobari, O.A., P. Zawar-Reza, A. Sturman, 2014. The global distribution of mineral dust and its impacts on the climate system: A review. Atmos. Res. 138, 152-165. https://doi.org/10.1016/j.atmosres.2013.11.007

Crone, S.F., J. Guajardo, R. Weber, 2006. A study on the ability of Support Vector Regression and Neural Networks to Forecast Basic Time Series Patterns. In: Proceedings of Artificial Intelligence in Theory and Practice, pp. 149-158.

Daisaku, U., 2016. Aerosol Optical Depth product derived from Himawari-8 data for Asian dust monitoring. Meteorol. Satell. Center Tech. Note. 61.

DeSouza‐Machado, S., L. Strow, B. Imbiriba, K. McCann, R. Hoff, S. Hannon, J. Martins, D. Tanré, J. Deuzé, F. Ducos, 2010. Infrared retrievals of dust using AIRS: Comparisons of optical depths and heights derived for a North African dust storm to other collocated EOS A‐Train and surface observations. J. Geophys. Res. Atmos. 115.

Di Noia, A., O.P. Hasekamp, G. van Harten, J.H.H. Rietjens, J.M. Smit, F. Snik, J.S. Henzing, J. de Boer, C.U. Keller, H. Volten, 2015. Use of neural networks in ground-based aerosol retrievals from multi-angle spectropolarimetric observations. Atmos. Meas. Tech. 8, 281-299. https://doi.org/10.5194/amt-8-281-2015

Du, W., J. Xin, M. Wang, Q. Gao, Z. Li, Y. Wang, 2008. Photometric measurements of spring aerosol optical properties in dust and non-dust periods in China. Atmos. Environ. 42, 7981-7987. https://doi.org/https://doi.org/10.1016/j.atmosenv.2008.06.043

Dubovik, O., M.D. King, 2000. A flexible inversion algorithm for retrieval of aerosol optical properties from Sun and sky radiance measurements. J. Geophys. Res. Atmos. 105, 20673-20696. https://doi.org/10.1029/2000JD900282

Ellrod, G.P., B.H. Connell, D.W. Hillger, 2003. Improved detection of airborne volcanic ash using multispectral infrared satellite data. J. Geophys. Res. Atmos. 108. https://doi.org/10.1029/2002jd002802

Friedman, J.H., 2001. Greedy function approximation: a gradient boosting machine. The Annals of Statistics. 29, 1189-1232.

Geurts, P., D. Ernst, L. Wehenkel, 2006. Extremely randomized trees. Machine learning. 63, 3-42. https://doi.org/10.1007/s10994-006-6226-1

Grainger, R.G., 2012. Some useful formulae for aerosol size distributions and optical properties. Lect. Notes (University of Oxford). 12-13.

Griggs, D.J., M. Noguer, 2002. Climate change 2001: the scientific basis. Contribution of working group I to the third assessment report of the intergovernmental panel on climate change. Weather. 57, 267-269.

Gu, Y., W.I. Rose, G.J.S. Bluth, 2003. Retrieval of mass and sizes of particles in sandstorms using two MODIS IR bands: A case study of April 7, 2001 sandstorm in China. Geophys. Res. Lett. 30. https://doi.org/10.1029/2003gl017405

Guo, J., M. Lou, Y. Miao, Y. Wang, Z. Zeng, H. Liu, J. He, H. Xu, F. Wang, M. Min, 2017. Trans-Pacific transport of dust aerosols from East Asia: Insights gained from multiple observations and modeling. Environ. Pollut. 230, 1030-1039. https://doi.org/10.1016/j.envpol.2017.07.062

Han, H.-J., B.J. Sohn, 2013. Retrieving Asian dust AOT and height from hyperspectral sounder measurements: An artificial neural network approach. J. Geophys. Res. Atmos. 118, 837-845. https://doi.org/10.1002/jgrd.50170

Hoerl, A.E., R.W. Kennard, 1970. Ridge Regression: Biased Estimation for Nonorthogonal Problems. Technometrics. 12, 55-67. https://doi.org/10.1080/00401706.1970.10488634

Holben, B.N., T.F. Eck, I. Slutsker, D. Tanre, J. Buis, A. Setzer, E. Vermote, J. Reagan, Y. Kaufman, T. Nakajima, 1998. AERONET—A federated instrument network and data archive for aerosol characterization. Remote Sens. Environ. 66, 1-16.

Hornik, K., M. Stinchcombe, H. White, 1989. Multilayer feedforward networks are universal approximators. Neural Networks. 2, 359-366. https://doi.org/https://doi.org/10.1016/0893-6080(89)90020-8

Hsu, N., M.J. Jeong, C. Bettenhausen, A. Sayer, R. Hansell, C. Seftor, J. Huang, S.C. Tsay, 2013. Enhanced Deep Blue aerosol retrieval algorithm: The second generation. J. Geophys. Res. Atmos. 118, 9296-9315.

Hsu, N.C., J. Lee, A.M. Sayer, N. Carletta, S.H. Chen, C.J. Tucker, B.N. Holben, S.C. Tsay, 2017. Retrieving near-global aerosol loading over land and ocean from AVHRR. J. Geophys. Res. Atmos. 122, 9968-9989. https://doi.org/https://doi.org/10.1002/2017JD026932

Hsu, N.C., J. Lee, A.M. Sayer, W. Kim, C. Bettenhausen, S.C. Tsay, 2019. VIIRS Deep Blue Aerosol Products Over Land: Extending the EOS Long-Term Aerosol Data Records. J. Geophys. Res. Atmos. 124, 4026-4053. https://doi.org/https://doi.org/10.1029/2018JD029688

Hsu, N.C., S.-C. Tsay, M.D. King, J.R. Herman, 2004. Aerosol properties over bright-reflecting source regions. IEEE Trans. Geosci. Remote Sens. 42, 557-569. https://doi.org/10.1109/TGRS.2004.824067

Kaufman, Y., A. Gitelson, A. Karnieli, E. Ganor, R. Fraser, T. Nakajima, S. Mattoo, B. Holben, 1994. Size distribution and scattering phase function of aerosol particles retrieved from sky brightness measurements. J. Geophys. Res. Atmos. 99, 10341-10356. https://doi.org/10.1029/94JD00229

Kaufman, Y.J., D. Tanré, L.A. Remer, E. Vermote, A. Chu, B. Holben, 1997a. Operational remote sensing of tropospheric aerosol over land from EOS moderate resolution imaging spectroradiometer. J. Geophys. Res. 102, 17051-17067.

Kaufman, Y.J., D. Tanré, L.A. Remer, E.F. Vermote, A. Chu, B.N. Holben, 1997b. Operational remote sensing of tropospheric aerosol over land from EOS moderate resolution imaging spectroradiometer. J. Geophys. Res. Atmos. 102, 17051-17067. https://doi.org/doi:10.1029/96JD03988

Kim, M., J. Kim, M.S. Wong, J. Yoon, J. Lee, D. Wu, P.W. Chan, J.E. Nichol, C.-Y. Chung, M.-L. Ou, 2014. Improvement of aerosol optical depth retrieval over Hong Kong from a geostationary meteorological satellite using critical reflectance with background optical depth correction. Remote Sens. Environ. 142, 176-187. https://doi.org/10.1016/j.rse.2013.12.003

King, M.D., Y.J. Kaufman, D. Tanré, T. Nakajima, 1999. Remote sensing of tropospheric aerosols from space: Past, present, and future. Bull. Am. Meteor. Soc. 80, 2229-2260.

Lanzaco, B.L., L.E. Olcese, G.G. Palancar, B.M. Toselli, 2017. An improved aerosol optical depth map based on Machine-Learning and MODIS data: Development and application in South America. Aerosol Air Qual. Res. 17, 1623–1636. https://doi.org/10.4209/aaqr.2016.11.0484

Lee, K., Y. Kim, W. von Hoyningen-Huene, J. Burrows, 2007. Spatio-temporal variability of atmospheric aerosol from MODIS data over Northeast Asia in 2004. Atmos. Environ. 41, 3959-3973.

Lee, K.H., J.E. Kim, Y.J. Kim, J. Kim, W. von Hoyningen-Huene, 2005. Impact of the smoke aerosol from Russian forest fires on the atmospheric environment over Korea during May 2003. Atmos. Environ. 39, 85-99.

Lee, K.H., Y.J. Kim, 2010. Satellite remote sensing of Asian aerosols: a case study of clean, polluted, and Asian dust storm days. Atmos. Meas. Tech. 3, 1771-1784. https://doi.org/10.5194/amt-3-1771-2010

Lee, K.H., Y.J. Kim, W. von Hoyningen‐Huene, 2004. Estimation of aerosol optical thickness over northeast Asia from Sea‐Viewing Wide Field‐of‐View Sensor (SeaWiFS) data during the 2001 ACE‐Asia intensive observation period. J. Geophys. Res. Atmos. 109.

Lee, K.H., K.T. Lee, 2015. Volcanic Ash Retrieval Using a New Geostationary Satellite. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. 40, 67. https://doi.org/10.5194/isprsarchives-XL-7-W4-67-2015

Lee, K.H., Z. Li, Y.J. Kim, A. Kokhanovsky, 2009. Atmospheric aerosol monitoring from satellite observations: a history of three decades. Atmospheric and biological environmental monitoring. Springer pp. 13-38.

Lee, S.-S., B. Sohn, 2012. Nighttime AOT retrieval for Asian dusts from MODIS IR measurements: An artificial neural network approach. Journal of the Meteorological Society of Japan. Ser. II. 90, 163-177.

Legrand, M., J. Bertrand, M. Desbois, L. Menenger, Y. Fouquart, 1989. The potential of infrared satellite data for the retrieval of Saharan-dust optical depth over Africa. J. Appl. Meteorol. 28, 309-319.

Legrand, M., M. Desbois, K. Vovor, 1988. Satellite detection of Saharan dust: Optimized imaging during nighttime. J. Clim. 1, 256-264.

Legrand, M., A. Plana‐Fattori, C. N'doumé, 2001. Satellite detection of dust using the IR imagery of Meteosat: 1. Infrared difference dust index. J. Geophys. Res. Atmos. 106, 18251-18274. https://doi.org/10.1029/2000JD900749

Li, J., M.S. Wong, K.H. Lee, J. Nichol, P. Chan, 2020a. Review of dust storm detection algorithms for multispectral satellite sensors. Atmos. Res. 250, 105398. https://doi.org/10.1016/j.atmosres.2020.105398

Li, R., L. Cui, H. Fu, Y. Meng, J. Li, J. Guo, 2020b. Estimating high-resolution PM1 concentration from Himawari-8 combining extreme gradient boosting-geographically and temporally weighted regression (XGBoost-GTWR). Atmos. Environ., 117434.

Lim, H., M. Choi, J. Kim, Y. Kasai, P. Chan, 2018. AHI/Himawari-8 Yonsei Aerosol Retrieval (YAER): Algorithm, Validation and Merged Products. Remote Sens. 10, 699.

Liu, H., Z. Fu, K. Yang, X. Xu, M. Bauchy, 2019a. Machine learning for glass science and engineering: A review. Journal of Non-Crystalline Solids: X. 4, 100036. https://doi.org/https://doi.org/10.1016/j.nocx.2019.100036

Liu, N., B. Zou, H. Feng, W. Wang, Y. Tang, L. Yu, 2019b. Evaluation and comparison of multiangle implementation of the atmospheric correction algorithm, Dark Target, and Deep Blue aerosol products over China. Atmos. Chem. Phys. 19, 8243-8268. https://doi.org/10.5194/acp-19-8243-2019

Lyapustin, A., Y. Wang, S. Korkin, D. Huang, 2018. MODIS Collection 6 MAIAC algorithm. Atmos. Meas. Tech. 11.

Lyapustin, A., Y. Wang, I. Laszlo, R. Kahn, S. Korkin, L. Remer, R. Levy, J. Reid, 2011. Multiangle implementation of atmospheric correction (MAIAC): 2. Aerosol algorithm. J. Geophys. Res. Atmos. 116.

Martínez, M.A., J. Ruiz, E. Cuevas, 2009. Use of SEVIRI images and derived products in a WMO Sand and dust Storm Warning System. IOP Conference Series: Earth and Environmental Science. 7, 012004. https://doi.org/10.1088/1755-1307/7/1/012004

Martins, V.S., A. Lyapustin, L.A. de Carvalho, C.C.F. Barbosa, E.M.L.d.M. Novo, 2017. Validation of high‐resolution MAIAC aerosol product over South America. J. Geophys. Res. Atmos. 122, 7537-7559. https://doi.org/10.1002/2016JD026301

Martius, G., C.H. Lampert, 2016. Extrapolation and learning equations. arXiv preprint arXiv. 1610:02995.

Mauceri, S., B. Kindel, S. Massie, P. Pilewskie, 2019. Neural network for aerosol retrieval from hyperspectral imagery. Atmos. Meas. Tech. 12, 6017-6036. https://doi.org/10.5194/amt-2019-228

Mhawish, A., T. Banerjee, M. Sorek-Hamer, A. Lyapustin, D.M. Broday, R. Chatfield, 2019. Comparison and evaluation of MODIS Multi-angle Implementation of Atmospheric Correction (MAIAC) aerosol product over South Asia. Remote Sens. Environ. 224, 12-28. https://doi.org/10.1016/j.rse.2019.01.033

Miller, S.D., T.L. Schmit, C.J. Seaman, D.T. Lindsey, M.M. Gunshor, R.A. Kohrs, Y. Sumida, D. Hillger, 2016. A sight for sore eyes: The return of true color to geostationary satellites. Bull. Am. Meteor. Soc. 97, 1803-1816. https://doi.org/10.1175/BAMS-D-15-00154.1

Pektas, A.O., H.K. Cigizoglu, 2017. Investigating the extrapolation performance of neural network models in suspended sediment data. Hydrological Sciences Journal. 62, 1694-1703. https://doi.org/10.1080/02626667.2017.1349316

Peyridieu, S., A. Chédin, V. Capelle, C. Tsamalis, C. Pierangelo, R. Armante, C. Crevoisier, L. Crépeau, F. Ducos, N. Scott, 2012. Characterization of dust aerosols in the infrared from IASI and comparison with PARASOL, MODIS, MISR, CALIOP, and AERONET observations. Atmos. Chem. Phys. 13, 6065-6082. https://doi.org/10.5194/acp-13-6065-2013

Peyridieu, S., A. Chédin, D. Tanré, V. Capelle, C. Pierangelo, N. Lamquin, R. Armante, 2010. Saharan dust infrared optical depth and altitude retrieved from AIRS: a focus over North Atlantic–comparison to MODIS and CALIPSO. Atmos. Chem. Phys. 10, 1953-1967. https://doi.org/10.5194/acp-10-1953-2010

Pierangelo, C., A. Chédin, S. Heilliette, N. Jacquinet-Husson, R. Armante, 2004. Dust altitude and infrared optical depth from AIRS. Atmos. Chem. Phys. 4, 1813-1822.

Pierangelo, C., Mishchenko, M., Balkanski, Y., & Chédin, A, 2005. Retrieving the effective radius of Saharan dust coarse mode from AIRS. Geophys. Res. Lett. 32. https://doi.org/10.1029/2005gl023425

Qu, J.J., X. Hao, M. Kafatos, L. Wang, 2006. Asian dust storm monitoring combining Terra and Aqua MODIS SRB measurements. IEEE Geosci. Remote S. 3, 484-486. https://doi.org/10.1109/lgrs.2006.877752

Reichstein, M., G. Camps-Valls, B. Stevens, M. Jung, J. Denzler, N. Carvalhais, Prabhat, 2019. Deep learning and process understanding for data-driven Earth system science. Nature. 566, 195-204. https://doi.org/10.1038/s41586-019-0912-1

Roskovensky, J., K. Liou, 2005. Differentiating airborne dust from cirrus clouds using MODIS data. Geophys. Res. Lett. 32. https://doi.org/10.1029/2005gl022798

Sandmeier, S., K.I. Itten, 1997. A physically-based model to correct atmospheric and illumination effects in optical satellite data of rugged terrain. IEEE Trans. Geosci. Remote Sens. 35, 708-717. https://doi.org/10.1109/36.581991

She, L., Y. Xue, X. Yang, J. Leys, J. Guang, Y. Che, C. Fan, Y. Xie, Y. Li, 2018. Joint Retrieval of Aerosol Optical Depth and Surface Reflectance Over Land Using Geostationary Satellite Data. IEEE Trans. Geosci. Remote Sens. 57, 1489-1501. https://doi.org/10.1109/TGRS.2018.2867000

Shenk, W.E., R.J. Curran, 1974. The Detection of Dust Storms Over Land and Water With Satellite Visible and Infrared Measurements. Mon. Weather. Rev. 102, 830-837. https://doi.org/10.1175/1520-0493(1974)102<0830:TDODSO>2.0.CO;2

Shin, S.K., M. Tesche, Y. Noh, D. Müller, 2019. Aerosol-type classification based on AERONET version 3 inversion products. Atmos. Meas. Tech. 12, 3789-3803. https://doi.org/10.5194/amt-12-3789-2019

Singhal, G., B. Bansod, L. Mathew, J. Goswami, B.U. Choudhury, P.L.N. Raju, 2019. Chlorophyll estimation using multi-spectral unmanned aerial system based on machine learning techniques. Remote Sensing Applications: Society and Environment. 15, 100235. https://doi.org/https://doi.org/10.1016/j.rsase.2019.100235

Sinyuk, A., B.N. Holben, T.F. Eck, D.M. Giles, I. Slutsker, S. Korkin, J.S. Schafer, A. Smirnov, M. Sorokin, A. Lyapustin, 2020. The AERONET Version 3 aerosol retrieval algorithm, associated uncertainties and comparisons to Version 2. Atmos. Meas. Tech. 13, 3375-3411. https://doi.org/10.5194/amt-13-3375-2020

Smirnov, A., B.N. Holben, T.F. Eck, O. Dubovik, I. Slutsker, 2000. Cloud-Screening and Quality Control Algorithms for the AERONET Database. Remote Sens. Environ. 73, 337-349. https://doi.org/10.1016/S0034-4257(00)00109-7

Su, X., L. Wang, M. Zhang, W. Qin, M. Bilal, 2021. A High-Precision Aerosol Retrieval Algorithm (HiPARA) for Advanced Himawari Imager (AHI) data: Development and verification. Remote Sens. Environ. 253, 112221. https://doi.org/https://doi.org/10.1016/j.rse.2020.112221

Sun, J., M. Zhang, T. Liu, 2001. Spatial and temporal characteristics of dust storms in China and its surrounding regions, 1960–1999: Relations to source area and climate. J. Geophys. Res. 106, 10325-10333. https://doi.org/10.1029/2000JD900665

Tanré, D., M. Herman, Y.J. Kaufman, 1996. Information on aerosol size distribution contained in solar reflected spectral radiances. J. Geophys. Res. Atmos. 101, 19043-19060. https://doi.org/https://doi.org/10.1029/96JD00333

Tao, M., L. Chen, Z. Wang, J. Wang, H. Che, X. Xu, W. Wang, J. Tao, H. Zhu, C. Hou, 2017. Evaluation of MODIS Deep Blue Aerosol Algorithm in Desert Region of East Asia: Ground Validation and Intercomparison. J. Geophys. Res. Atmos. 122, 10,357-310,368. https://doi.org/https://doi.org/10.1002/2017JD026976

Taylor, M., S. Kazadzis, A. Tsekeri, A. Gkikas, V. Amiridis, 2014. Satellite retrieval of aerosol microphysical and optical parameters using neural networks: a new methodology applied to the Sahara desert dust peak. Atmos. Meas. Tech. 7, 3151-3175. https://doi.org//10.5194/amt-7-3151-2014

Tegen, I., A.A. Lacis, 1996. Modeling of particle size distribution and its influence on the radiative properties of mineral dust aerosol. J. Geophys. Res. 101, 19237-19244. https://doi.org/10.1029/95jd03610

Verrelst, J., J. Muñoz, L. Alonso, J. Delegido, J.P. Rivera, G. Camps-Valls, J. Moreno, 2012. Machine learning regression algorithms for biophysical parameter retrieval: Opportunities for Sentinel-2 and-3. Remote Sens. Environ. 118, 127-139. https://doi.org/10.1016/j.rse.2011.11.002

von Hoyningen-Huene, W., M. Freitag, J.B. Burrows, 2003. Retrieval of aerosol optical thickness over land surfaces from top-of-atmosphere radiance. J. Geophys. Res. Atmos. 108. https://doi.org/10.1029/2001JD002018

Wald, A.E., Y.J. Kaufman, D. Tanré, B.C. Gao, 1998. Daytime and nighttime detection of mineral dust over desert using infrared spectral contrast. J. Geophys. Res. Atmos. 103, 32307-32313. https://doi.org/10.1029/98JD01454

Wei, J., Z. Li, A. Lyapustin, L. Sun, Y. Peng, W. Xue, T. Su, M. Cribb, 2021. Reconstructing 1-km-resolution high-quality PM2.5 data records from 2000 to 2018 in China: spatiotemporal variations and policy implications. Remote Sens. Environ. 252, 112136. https://doi.org/https://doi.org/10.1016/j.rse.2020.112136

William, E.S., J.C. Robert, 1974. The Detection of Dust Storms Over Land and Water With Satellite Visible and Infrared Measurements. Mon. Weather. Rev. 102, 830-837. https://doi.org/10.1175/1520-0493(1974)102<0830:TDODSO>2.0.CO;2

Witten, I.H., E. Frank, M.A. Hall, C.J. Pal, 2017. Chapter 7 - Extending instance-based and linear models. In: Witten, I.H., Frank, E., Hall, M.A., Pal, C.J. (Eds.), Data Mining (Fourth Edition). Morgan Kaufmann pp. 243-284.

Wong, M.S., J.E. Nichol, K.H. Lee, 2011. An operational MODIS aerosol retrieval algorithm at high spatial resolution, and its application over a complex urban region. Atmos. Res. 99, 579-589. https://doi.org/10.1016/j.atmosres.2010.12.015

Wu, L., J. Fan, 2019. Comparison of neuron-based, kernel-based, tree-based and curve-based machine learning models for predicting daily reference evapotranspiration. PLoS ONE. 14, e0217520. https://doi.org/10.1371/journal.pone.0217520

Xia, F., W. Zhang, F. Li, Y. Yang, 2008. Ranking with decision tree. Knowledge and Information Systems. 17, 381-395. https://doi.org/10.1007/s10115-007-0118-y

Xiao, F., M.S. Wong, K.H. Lee, J.R. Campbell, Y.K. Shea, 2015. Retrieval of dust storm aerosols using an integrated Neural Network model. Comput. Geosci. 85, 104-114. https://doi.org/10.1016/j.cageo.2015.02.016

Xiao, X., T. Zhang, X. Zhong, W. Shao, X. Li, 2018. Support vector regression snow-depth retrieval algorithm using passive microwave remote sensing data. Remote Sens. Environ. 210, 48-64. https://doi.org/https://doi.org/10.1016/j.rse.2018.03.008

Xu, M., P. Watanachaturaporn, P.K. Varshney, M.K. Arora, 2005. Decision tree regression for soft classification of remote sensing data. Remote Sens. Environ. 97, 322-336. https://doi.org/https://doi.org/10.1016/j.rse.2005.05.008

Xu, X., J. Wang, J. Zeng, R. Spurr, X. Liu, O. Dubovik, L. Li, Z. Li, M.I. Mishchenko, A. Siniuk, 2015. Retrieval of aerosol microphysical properties from AERONET photopolarimetric measurements: 2. A new research algorithm and case demonstration. J. Geophys. Res. 120, 7079-7098. https://doi.org/10.1002/2015JD23108

Yao, Z., J. Li, H.J. Han, A. Huang, B. Sohn, P. Zhang, 2012. Asian dust height and infrared optical depth retrievals over land from hyperspectral longwave infrared radiances. J. Geophys. Res. Atmos. 117.

Yoshida, M., M. Kikuchi, T.M. Nagao, H. Murakami, T. Nomaki, A. Higurashi, 2018. Common Retrieval of Aerosol Properties for Imaging Satellite Sensors. Journal of the Meteorological Society of Japan. Ser. II., 193-209. https://doi.org/10.2151/jmsj.2018-039

Zamani Joharestani, M., C. Cao, X. Ni, B. Bashir, S. Talebiesfandarani, 2019. PM2.5 Prediction Based on Random Forest, XGBoost, and Deep Learning Using Multisource Remote Sensing Data. Atmosphere. 10, 373.

Zhang, P., N.-m. Lu, X.-q. Hu, C.-h. Dong, 2006. Identification and physical retrieval of dust storm using three MODIS thermal IR channels. Glob. Planet. Chang. 52, 197-206. https://doi.org/10.1016/j.gloplacha.2006.02.014

Zhang, Z., W. Wu, M. Fan, J. Wei, Y. Tan, Q. Wang, 2019. Evaluation of MAIAC aerosol retrievals over China. Atmos. Environ. 202, 8-16. https://doi.org/10.1016/j.atmosenv.2019.01.013