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AI-Driven Remote Sensing for Dust Storm Monitoring: Methods, Challenges, and Future Perspectives

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Abstract. Dust storms develop rapidly and can affect transport, ecosystems, and public health over large areas. The integration of satellite remote sensing and artificial intelligence (AI) has significantly improved capabilities in dust storm identification, parameter retrieval, and short-term forecasting. This paper reviews how AI algorithms have been applied to remote sensing monitoring of dust storms. The review first summarizes the remote sensing response characteristics of dust aerosols and the primary data sources. It then focuses on machine learning-based pixel classification and parameter retrieval, deep learning-based dust mask segmentation and short-term forecasting, and the application of physics-guided hybrid methods in dust storm monitoring. The review also discusses the applications of these dust monitoring products and it points out several remaining problems, including identification instability in complex environments, lack of labeled samples, the underestimation of extreme dust events, and the lack of physical consistency in short-term forecasts. Future studies should focus on improving joint observations of multi-source data, building cross-regional datasets, expanding the pool of extreme event samples, and developing interpretable short-term forecasting models. Such progress will help improve the quantification, continuous observation and practical application of AI-based dust storm remote sensing monitoring.

Keywords: Artificial Intelligence, Remote Sensing, Dust Storm Detection, Dust Aerosol Retrieval, Dust Nowcasting

1. Introduction

Dust particles can travel over long distances through the atmosphere and affect air quality, traffic safety, ecosystems, and human health at regional or even intercontinental scales. Due to the rapid formation, large spatial coverage, and fast movement of dust storms, continuous monitoring with broad spatial coverage is required. Conventional dust detection methods usually rely on brightness temperature differences, spectral ratios, dust indices and Dust RGB; they can also be combined with radiative transfer models and lookup tables to estimate parameters such as aerosol optical depth / aerosol optical thickness (AOD/AOT). But their performance can vary with threshold selection, surface albedo, cloud cover, and viewing geometry, which makes detection and retrieval unstable in some scenes [1, 2].

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The introduction of artificial intelligence has shifted dust storm remote sensing monitoring from rule-based approaches to data-driven learning. In many studies, machine-learning models use satellite bands, surface information, spectral indices, and meteorological variables to detect dust or retrieve parameters such as AOD/AOT and effective radius. Deep learning models, including CNNs, U-Nets, models with attention mechanisms, and Transformers have further improved the ability to extract spatial textures, boundary patterns, and contextual information. These models have therefore been applied to dust-mask extraction, aerosol retrieval, transport-path prediction, and early warning products. This review focuses on the application of AI in satellite dust storm monitoring and summarizes the recent advances in AI algorithms for dust detection, mask extraction, aerosol parameter retrieval, event tracking and short-term forecasting.

2. Remote sensing data for AI-driven dust monitoring

2.1. Physical and spectral observability of dust aerosols

The remote sensing detectability of dust aerosols mainly relies on its spectral, thermal infrared and vertical structure characteristics. The visible and short-wave IR regions give clues about the scattering and absorbing of solar radiation by dust, which can be applied for identification of dust plumes and estimation of the aerosol load like AOD and AOT. The thermal IR region has high sensitivity to the absorption, emission and brightness difference of dust particles, thus enabling day- and night-time detection of dust and estimation of parameters such as optical depth, particle size and altitude [2, 3]. LiDAR distinguishes the kind and vertical position of dust particles through backscatter, depolarization ratio and vertical profile data [4]. In short, these different remote sensing responses together serve as the basis for dust monitoring based on remote sensing.

2.2. Multi-platform sensors and data configurations

Dust storm monitoring depends on multi-source remote sensing observations, and various sensors have different characteristics in respect to spatial coverage, temporal resolution, spectral configuration and the kinds of missions they can undertake. The polar-orbiting multispectral sensors like MODIS and VIIRS supply abundant data in the visible, near-infrared, short-wave infrared and thermal infrared regions, which are suitable for dust detection, mask generation and aerosol parameters estimation [2]. The geostationary meteorological satellites such as Himawari-8/9, FY-4A and GOES-16 have a high temporal resolution and are more appropriate for the continuous observation of the occurrence, evolution and transportation of dust storms [5-7]. Their frequent observations also serve as an essential data source for short-term forecasting and nowcasting tasks [8, 9]. The CALIOP active lidar system on board the CALIPSO provides vertical profiles and depolarization ratio data, which are usually utilized for aerosol type identification, dust-cloud discrimination and verification of the training labels [4].

2.3. Multidimensional data requirements of AI models

Various artificial intelligence techniques need to consider the organization of the data. In classical machine learning, feature vectors are usually defined beforehand, and the performance of the model is affected by the of features like spectral bands, indices, geometric parameters and meteorological elements; deep learning can extract spatial textures and contextual information from multi-channel images or temporal grids, which is appropriate for mask segmentation, spatiotemporal forecasting

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and image generation; physics-oriented methods also include radiative transfer simulations, reanalysis data and ground-based observations to enlarge the sample, constrain the retrieval or correct the biases. In summary, the data needs for the artificial intelligence based dust storm detection are tending to be a data system which combines multiple origins, multi-temporal observations and physical constraints.

3. AI methods for dust monitoring: a categorized review

3.1. Traditional machine learning methods

Traditional machine learning represents the early stages of AI applications in dust storm remote sensing monitoring. Such methods typically begin by organizing satellite bands, brightness temperatures, band combinations, and meteorological or surface variables into feature vectors, and then use models such as SVM, SVR, ANN, and RF to perform pixel classification or estimate dust storm parameters. Compared to the fixed-threshold method, this type of method can establish more flexible classification relationships in a multidimensional feature space, but it relies heavily on predefined features.

3.1.1. Feature-vector-based pixel-level dust classification

Initial studies regarded dust detection as a pixel classification task, arranging raw spectral bands, brightness and temperature channels, spectral combinations or thermal infrared features into feature vectors, which were subsequently fed into machine learning models for classification.

Early studies, such as Rivas-Perea, Rosiles, and Cota-Ruiz [10] used the MODIS mid-IR and thermal-IR bands to identify dust storms using LP-SVR. Later, Souri and Vajedian [11] further trained a random forest model using multiple MODIS bands in the visible, near-infrared, short-wave infrared, and thermal infrared ranges, and compared it with various physical threshold methods.

Compared to the aforementioned study, which directly inputs raw bands, El-ossta, Qahwaji, and Ipson [12] input MODIS reflectance bands and brightness-temperature difference features into an ANN to improve the distinction between dust and sandy surfaces. Shi et al. [13] conducted a further systematic evaluation of MODIS multispectral data and their composite features, and used SVM to select optimal input features for dust detection. This reflects a shift from "empirical selection of features" to "systematic optimization of feature combinations."

Overall, these methods are simple in structure and highly interpretable, but model performance remains limited by the predefined bands, indices, and combinations of candidate features.

3.1.2. Improvement of the generalization capabilities of machine learning in dust detection

A dust detection model trained for one region or one sensor often loses accuracy when it is applied to another sensor, surface background, or viewing condition. For this reason, generalization has become a practical issue in machine-learning-based dust detection. The optical properties of dust may vary between source regions and downstream areas, and there is also confusion between dust and clouds, bright surfaces, and desert backgrounds. A classifier trained under one set of conditions may therefore perform poorly in another region or with another sensor. Ma, Gong, and Mao [14] dealt with this issue using the vertical-profile data of CALIPSO/CALIOP and transfer learning. They first classified dust aerosols from clouds by using SVM based on the vertical profile data of

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CALIPSO/CALIOP, and then employed TrAdaBoost transfer learning to enhance the classification accuracy from the source areas to the downstream regions.

Moreover, some researchers have tried to use machine learning techniques to integrate multi-source data and non-reflection bands. Choi et al. [15] fused the TROPOMI and MODIS data with a random forest (RF) model for the classification of different aerosol types, identifying dust as one of several aerosol types. Berndt et al. [7] also employed the GOES-16 ABI IR channel together with an RF model to identify nocturnal dust outbreaks. These investigations indicate that machine learning approaches can deal with more complicated dust storms via transfer learning, multi-source combination and enhancement of infrared features.

3.1.3. Shallow neural networks for dust retrieval and integrated monitoring

In addition to pixel-based classification, shallow neural networks are also employed for the retrieval of optical parameters of dust storms. ANN and MLP-BP models are well-suited for learning nonlinear relationships between remote sensing observations and continuous variables, and are therefore frequently used to estimate AOT, AOD, or other dust-related aerosol parameters. Xiao et al. [16] developed a "detection–retrieval–trajectory analysis" workflow. In this workflow, an integrated neural network framework first identifies dust pixels, then inverts the 550 nm dust AOT for those pixels, and finally combines the results with HYSPLIT simulations to reconstruct dust transport trajectories. Yao et al. [17] used AIRS hyperspectral IR brightness and a BP-ANN for the retrieval of nighttime dust aerosols. More recent studies have further compared the differences between ANNs and other traditional machine learning models, including the study by Li et al. [18]. This study uses data from Himawari-8/AHI to construct a set of 47 input features—including raw observations, dust indices, temporal anomalies, observation geometry, and DEM data—for the retrieval of dust AOT and effective radius reff, and compares six models: ANN, XGBoost, Extra Trees, RF, SVR, and Ridge. The results show that ANN performs best overall in both AOT and reff retrievals, indicating that ANN is better able to fully utilize spectral and temporal anomaly information.

3.1.4. Unsupervised learning for dust event tracking and mixed-pixel analysis

Unsupervised learning is primarily used for organizing dust storm events and analyzing mixed pixels when large-scale manual labeling is unavailable. AlNasser and Entekhabi [19] estimated the variations in the relative background levels of the PDI dust index using SEVIRI Dust RGB data to emphasize the significantly increased dust signals, and then used DBSCAN to group adjacent dust pixels into different dust events according to their spatial and temporal closeness, in order to study the movement routes of dust and identify possible source regions. For the hybrid pixel segmentation tasks, Li, Wong, and Nazeer [20] put forward the PISOM method, which integrates physical indices with SOM to distinguish dust-like pixels and calculate the proportions of dust, cloud and surface-related components in mixed pixels. Generally, unsupervised methods can decrease the dependence on manual labeling and are appropriate for tasks like dust storm event classification, source area investigation and the interpretation of mixed pixels.

Simple and efficient traditional machine-learning techniques have a limitation that the models mainly rely on individual pixels, and it is difficult for these methods to recognize and acquire the texture, boundary patterns and spatial contextual information in remote sensing images.

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3.2. Deep learning for dust detection, retrieval, and nowcasting

Deep learning has led to the development of dust storm remote sensing research from pixel-based classification based on manually selected features to dust mask segmentation and the forecasting of future dust storm paths. The use of CNNs, U-Nets, Transformers and generative models has allowed the application of AI methods to not only identify if a single pixel is dust, but also to describe the spatial range, boundary pattern and temporal change of dust plumes.

3.2.1. CNN-based pixel-level dust detection

Unlike the traditional single-pixel feature classification, CNNs use the local image patches around the target pixel as input and decide whether the central pixel is dust according to the spectral and spatial textures in the neighboring region. Jiang et al. [21] developed a CNN model based on the FY-4A/AGRI multi-channel observations to distinguish the central pixel as either dust or non-dust. Zhen et al. [6] also integrated CNNs with Long Short-Term Memory (LSTM) networks to include the time-series information and improve the detection of dust storms.

3.2.2. Encoder–decoder and attention-enhanced networks for dust mask segmentation

U-Net, DeepLabv3+, and their variants have further advanced dust detection to the stage of semantic segmentation. The encoder-decoder architecture can first extract high-level semantic features through downsampling, then restore spatial resolution through upsampling, thereby directly outputting a dust mask. Ramasubramanian et al. [22] used U-Net for day-night dust event segmentation to extract dust masks.

Later studies further enhanced segmentation capabilities through multi-model ensemble and attention mechanisms. Bandara [23] combined U-Net, DeepLabv3+, and Swin U-Net into an integrated model for binary semantic segmentation, aiming to combine local details, multi-scale context, and global modeling capabilities. In the study by Mahmoud et al. [24], Bi-LSTM coupled with gating attention was introduced to optimize the U-Net framework. The improved network can accurately model the evolving process of dust storms, prioritize salient regions and reduce disturbances from irrelevant background content. Consequently, its segmentation capability is more reliable than that of the standard U-Net.

3.2.3. Deep learning for dust-related retrieval

Deep learning has also been applied to quantitative retrieval during dust events, estimating variables such as AOD, PM10, and PM2.5. Fan et al. [25] proposed AeroTrans-MSG, a Transformer-based transfer learning model that retrieves hourly 550 nm AOD from MSG-1/SEVIRI imagery. The model was pre-trained with MERRA-2 data and then fine-tuned with ground-based observations. Although it is not designed only for dust storms, its hourly AOD retrievals can help describe aerosol loading during dust events. Peng et al. [26] proposed OnOrbitDustNet for dust monitoring. This model combines dust event detection with multi-task retrieval of PM10 and PM2.5, forming an on-orbit workflow that links dust detection, PM10/PM2.5 retrieval, and rapid warning-oriented product generation. Its tail-aware loss function was used to reduce the underestimation of high-concentration dust samples.

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3.2.4. Spatiotemporal and generative models for dust nowcasting

In practical applications, it is crucial to predict the potential extent of future dust storms. Thus, in recent years, some deep learning research has shifted from dust monitoring to predicting future dust trajectories, dust masks, or Dust RGB images.

Yarmohamadi et al. [27] constructed a CNN model based on MERRA-2 dust AOT imagery and geospatially contextual variables such as relative humidity, surface temperature, wind speed, and wind direction to predict dust transport pathways for the next 6 to 24 hours. Alshaibani, Mutawa, and Almatar [8] further used SEVIRI Dust RGB and a Pix2Pix-inspired GAN to predict the next frame of Dust RGB imagery, demonstrating the potential of generative models in dust storm image prediction. Hermes et al. [9] used a diffusion model to recursively generate future Dust RGB images. These studies indicate that generative and spatiotemporal models are expanding AI-based dust storm monitoring from current detection to the prediction of future developments.

3.3. Physics-guided and hybrid methods

Although traditional machine learning and deep learning methods have significantly improved capabilities in dust detection, segmentation, and retrieval, data-driven models still face challenges in areas such as insufficient data, scarcity of extreme events, cross-regional generalization, and physical interpretability. Hence, recent research has begun to integrate physical knowledge more deeply into AI frameworks.

In retrieval tasks, these methods usually use a "prior learning and ground-based correction" method. Tang et al. [28] put forward the AIRTrans algorithm, which integrates a radiative transfer model (RTM) to produce simulated data including different kinds of aerosols and surface conditions for pre-training an artificial neural network (ANN), and then refines the model by using ground-based observations from AERONET to accomplish the simultaneous retrieval of Himawari-8 AOT and fine-mode fraction (FMF). Similarly, Fan et al. [25] suggested AeroTrans-MSG which adopts a similar strategy to enhance the generalization ability of hourly AOD retrieval by means of pre-training on reanalysis products and refining with ground-based AOD observations.

In addition, physical simulations can be utilized to enhance dust detection. Jin et al. [5] performed forward radiation transfer simulations during the detection process, training an ANN with the simulated clear-sky brightness temperatures and the thermal infrared brightness temperatures from AHI and surface information, which improves both day and night dust detection, particularly for optically thin dust. Generally, physically guided and hybrid methods provide a novel approach for remote sensing of dust by combining artificial intelligence in a data-driven way with data learning and physical constraints.

Overall, physically guided and hybrid methods indicate a change in AI-based dust remote sensing from a data-driven method to one which integrates data learning with physical constraints.

4. Applications and challenges

4.1. Typical application scenarios of dust storm monitoring

The above mentioned methods can be applied to obtain a variety of dust remote sensing data which are beneficial for different monitoring purposes. Dust mask extraction data can be utilized to estimate the spatial distribution of dust plumes promptly, serving as basic information for the mapping of affected regions and guiding the emergency response; the retrieval data such as

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AOD/AOT, effective radius, dust plume height and PM10/PM2.5 can be used to evaluate the dust load and its influence on the surface air quality; the aerosol classification data can be employed for the determination of the sources and investigation of the pollution processes; the products concerning the tracking and short-term prediction of dust storms can be used to depict the displacement of dust storms, locate possible source areas and forecast the extent of the future effects, thus offering assistance for the early warnings of transportation and public health.

4.2. Current key challenges and future directions

Although AI techniques are currently extensively applied in the extraction of dust masks, retrieval of parameters and short-term prediction, their stability, generalizability and physical reliability still need to be enhanced.

Primary existing obstacles involve unstable masking results under complex conditions, insufficient cross-regional data, underestimation of high values in retrieval models, and insufficient physical constraints in generative model-based dust storm prediction. Further studies therefore should focus on fusing multi-source remote sensing data, building benchmark datasets that work across regions and sensors, including more severe-event samples, and adding physical constraints to forecasting models.

4.2.1. Uncertainty in dust masking under complex background conditions

Detection of dust is also difficult under cloudy weather, on clear sandy areas, at night and when the dust is extremely fine. Jin et al. [5], Zhen et al. [6], and Mahmoud et al. [24] stated that thin dust, cloud cover, sandy backgrounds, mixture of dust and cloud and low spatial resolution might cause misidentification or unsatisfactory segmentation.

Future research can integrate thermal infrared simulations, clear-sky background restrictions and physically relevant indices to enhance the detection of weak dust. Moreover, observations from different sources may be beneficial. Geostationary images can assure the temporal continuity, multispectral sensors can distinguish the spectra and lidar profiles can supply vertical information for the construction or verification of labels. All these data sources may improve the masking of dust in complicated backgrounds.

4.2.2. Dependence on manually annotated training labels and limited cross-regional generalization

Supervised learning-based dust detection and segmentation models mainly rely on accurate labels. The studies of Bandara [23] and Ramasubramanian et al. [22] train deep segmentation models using manually labeled dust masks which are costly to acquire and may be influenced by selection bias and variations in annotators' experience. Similarly, Jiang et al. [21] also mention that the lack of sufficient training samples might affect the model's performance in different regions and conditions.

In the future, it is necessary to set up a cross-regional, cross-sensor reference database for dust storms and enhance the accuracy of the labels by combining lidar data and ground-based observations. The LSDSSIMR database established by Bai et al. [29] combines the multi-channel images of FY-4A, dust event labels and the reanalysis data of ERA5/MERRA-2, offering important data support for the detection and forecast of dust with high temporal resolution.

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4.2.3. Underestimation of extreme dust values in dust-related retrieval tasks

Dust-related parameters are usually underestimated in severe dust storms and high concentrations. Li et al. [18] showed that high-value samples may lead to errors in the retrieval of dust AOT and effective radius. In the study by Fan et al. [25], although hourly AOD retrievals can successfully describe the diurnal variation of extreme aerosol events like dust storms, the models still require higher stability in dealing with severe pollution situations. Peng et al. [26] pointed out that the PM10/PM2.5 samples have a long-tail distribution and the standard loss functions often underestimate the concentrations in the core areas of dust storms.

In the future, the sensitivity of the model to high AOD/AOT and high PM concentrations can be improved through the addition of extreme event samples, reweighting of samples and use of tail-aware loss functions. Moreover, the accuracy in retrieving extreme high values can be enhanced by integrating radiative transfer simulations and reanalysis data.

4.2.4. Lack of physical consistency in generative model-based dust nowcasting

Generative models provide an innovative method for short-term dust storm prediction, but the prediction procedures now do not have any physical constraints. Alshaibani et al. [8] and Hermes et al. [9] applied GANs and diffusion models to forecast the future Dust RGB images respectively; however, neither considered the external dynamic meteorological factors such as wind fields, humidity or source-area conditions. Therefore, the generative dust storm forecasting still has a difference between the visual credibility and the physical reliability. Future investigations can include wind fields, humidity, surface temperature and source-area conditions in GAN-, diffusion- or Transformer-based systems to constrain the transport, dispersion and dissipation of dust plumes. These physical constraints will enable short-term dust forecasting to be based on more physically consistent predictions, enhancing the accuracy of the forecast results.

5. Conclusion

This review examines the application of AI techniques in satellite dust storm monitoring. The studied papers show advancements from the pixel-wise classification using hand-designed features to the extraction of dust masks, retrieval of parameters and short-term prediction. Furthermore, recent research incorporates physical prior information to lessen the shortcomings of purely data-driven models.

Several issues still exist in present research. The dust masks are unstable in complicated backgrounds, the labeled samples are limited, the high values are frequently underestimated during serious dust storms, and the generative model-based predictions may not conform to the physical transport processes. In the future, the investigations should give greater attention to the cross-regional data sets, the severe-event samples, the multiple sources of observations and the physical constraints in the forecasting models. For operational applications, AI-based dust monitoring systems should integrate the detection, retrieval, tracking and forecasting instead of treating them as separate tasks. This combined method will improve the practical use of AI-based dust monitoring in operational dust-storm risk management.

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