



# Dust detection algorithm for the EarthCARE Multi-Spectral Imager over the ocean

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**Abstract.** Following the launch of the EarthCARE (Earth Clouds, Aerosols and Radiation Explorer) satellite in May 2024, the Multi-spectral Imager (MSI) supplements the vertical information retrieved from the Atmospheric Lidar (ATLID) and the Cloud Profiling Radar (CPR) instruments by providing information on cloud and aerosol properties in the across-track direction. MSI features a 150 km swath and a spatial resolution of 500 m across its four solar and three thermal channels. The operational cloud mask algorithm does not distinguish between clouds and aerosols, potentially leading to misclassifications of thick aerosol layers over ocean originating from dust storms, wildfires, or volcanic eruptions as clouds. Existing dust detection algorithms rely on spectral channels that are not available on MSI. This study therefore introduces a dust detection algorithm over ocean for MSI based on a random forest (RF) classification model that operates with the reduced spectral information available from the instrument. RF is a machine-learning approach that constructs multiple decision trees, whose outcomes are aggregated to generate accurate and reliable predictions. Pre-launch of the EarthCARE mission, a precursor dust detection algorithm was developed with Moderate-resolution Imaging Spectroradiometer (MODIS) data, using channels similar to those of MSI and adjusted to match MSI's swath dimensions. Two case studies of dust storm outbreaks captured by MSI demonstrate the model's capability and highlight its potential for operational use.

## 1 Introduction

Atmospheric mineral dust is a key component of the Earth's climate system (Miller and Tegen, 1998), influencing radiation balance, cloud microphysics, and biogeochemical cycles (Boucher et al., 2013). A particular challenge in dust detection over oceans arises from its spectral similarity to certain cloud types, making a reliable separation between mineral dust and clouds essential for accurate aerosol retrievals.

With the launch of the joint ESA and JAXA EarthCARE satellite on May 28, 2024, the multi-spectral imager (MSI) was brought into Earth orbit. On the seventh mission of the ESA Earth Explorers program, MSI is on a single platform along with a high-spectral-resolution atmospheric lidar, a Doppler cloud profiling radar and a three-view broadband radiometer, enabling synergistic products (Illingworth et al., 2015). The mission's main objectives are to expand our understanding of the interaction of clouds, aerosols and radiation, and to improve weather and climate models (Wehr et al., 2023). MSI is used to derive cloud properties such as cloud optical depth, cloud top height, cloud phase and cloud type as well as aerosol properties of clear sky pixels, including aerosol optical depth (AOD) (Hünérbein et al., 2023, 2024; Docter et al., 2023). Tests of the cloud detection

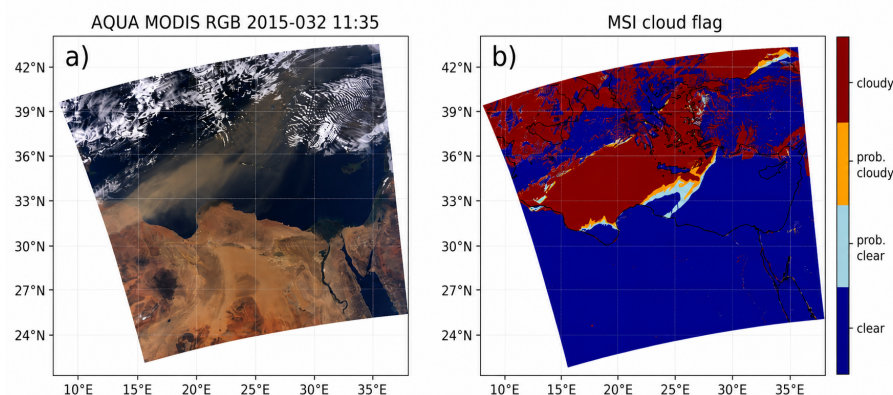


algorithm of MSI in dust storm scenarios have revealed that dust layers are often misclassified as clouds, leading to the incorrect assignment of cloud properties to dusty pixels as shown in Fig. 1. The MSI cloud mask algorithm was applied to a scene from the Moderate Resolution Imaging Spectroradiometer (MODIS) over the mediterranean sea with a thick dust layer using only spectral channels analogous to those of MSI. In this case, the dust layer, visibly distinguishable from ocean and clouds by its brown color, was predominantly identified as clouds by the MSI-based cloud mask. This highlights the need for a reliable distinction between dust and clouds, which is essential for accurate retrieval of both aerosol and cloud properties. To address this, a dedicated dust detection algorithm, tailored to the spectral and observational characteristics of MSI, is needed. For the detection of dust, various spectral tests using ratios and normal differences are often combined into a single algorithm, e.g., in the MxD35 L2 MODIS cloud mask product (Ackerman et al., 1998; Zhao et al., 2010) or in Zhou et al. (2020). Recent studies on dust detection have increasingly focused on machine learning algorithms. Lee et al. (2021) compares five different machine learning techniques for dust detection with MODIS over land and ocean. The random forest (RF) classification model was found to be among the best-performing algorithms and has also been used in other studies (e.g., Souri and Vajedian, 2015). for dust detection in different applications. Souri and Vajedian (2015) demonstrated that an RF model built using a subset of MODIS spectral bands over the Middle East outperformed traditional physically based algorithms. Given the limited number of spectral channels available on MSI compared to sensors like Visible Infrared Imaging Radiometer Suite (VIIRS) or MODIS, particularly in the visible range, there is a clear need for a tailored detection approach. In anticipation of MSI data availability, a precursor dust detection algorithm for ocean pixels was developed based on an RF model. This retrieval method utilizes the seven MSI channels, spanning from the visible (VIS) to the thermal infrared (TIR) spectral region. The instrument has central wavelengths at 670 nm (VIS), 865 nm (NIR), 1650 nm (SWIR-1), 2210 nm (SWIR-2), 8.8  $\mu\text{m}$  (TIR-1), 10.8  $\mu\text{m}$  (TIR-2), and 12.0  $\mu\text{m}$  (TIR-3) (see Table 1). In this study, MODIS observations were used as a proxy for MSI measurements, restricted to MSI-like spectral channels. The dataset employed is described in Section 2. Section 3 outlines the configuration of the RF model. In Section 4, the performance of the RF-based dust detection algorithm is evaluated using two case studies based on real MSI data capturing a dust layer over the Mediterranean Sea, observed simultaneously by MSI, ATLID, and MODIS, enabling cross-instrument comparisons and verification. The results are compared against the MxD35 dust flag for reference. A summary and discussion of the findings is provided in Section 5.

## 2 Data

### 2.1 Data selection

For this study, the year 2021 has been examined to identify prominent dust events across major dust-prone regions using a set of 67 MODIS scenes (see Figure 2(a)). The data was split into 60 MODIS cases for training and 7 for testing and tuning the models. Both sets include pixels of dust, cloud, clear sky, smoke and volcanic plume. The preliminary selection of cases was performed via NASA Worldview (Earth Science Data and Information System (ESDIS), 2026), which offers true-color RGB composites generated from MODIS observations in conjunction with the integrated Deep Blue aerosol typing product retrieved from VIIRS data (Hsu et al., 2019). Additional dust cases from 2003 to 2024 have been compiled for regions where



**Figure 1.** True color image of a thick dust plume over the Mediterranean in (a), along with results of the MSI cloud detection algorithm applied to MODIS channels similar to MSI in (b), illustrating the classification of dust pixels as clouds.

dust storm occurrences are relatively infrequent. These events have been identified using NASA Earth Observatory (NASA Earth Observatory, 1999) and previous studies focused on aerosol detection (Zhou et al., 2020). Within the same period, non-dust aerosol samples, such as smoke and volcanic ash, have also been collected (see Figure 2(b)). Calibrated radiances of MODIS Terra/Aqua Level 1B (L1B; MODIS Science Data Support Team (SDST), 2017b, a, ; abbreviated to MxD21km) have been used for generating input for the RF model using reflectances and brightness temperatures from channels similar to those of MSI. Tab. 1 provides an overview of the central wavelengths of the MSI channels and the corresponding MODIS channels. Additionally, we used the AOD from MxD04-3K (Levy and Hsu, 2015) for tailoring the selection of dust pixels and to subsequently exclude thinner dust layers. The suspended dust flag from the MxD35 cloud mask (Ackerman, 2015), from here MODIS dust flag, has been applied to the selected scenes to verify the presence of dust and is further used for comparison with the RF dust detection. For the verification of the RF dust detection, we use the following EarthCARE products along with collocated MODIS products: From MSI, M-RGR (Bley et al., 2026) serves as input for our dust mask retrieval and M-CM (Hünerbein et al., 2023) for evaluation of the cloud mask over dust plumes. ATLID was used to check the sensitivity of RF dust mask to AOD, which was derived using A-TC and A-EBD (Donovan et al., 2024).

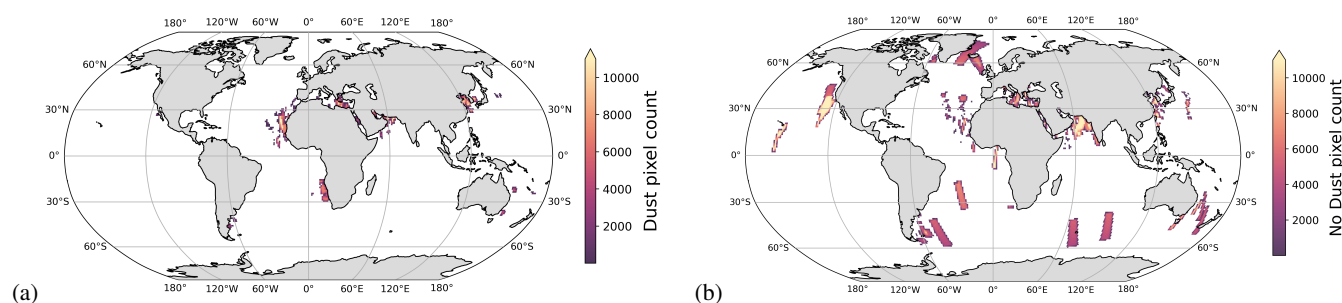
Single-channel reflectances, the Normalized Difference Dust Index (NDDI; Han et al., 2013) and the brightness temperature difference ( $10.8\mu m - 12.0\mu m$ ), have been used on the selected MODIS scenes to manually identify dust pixels. To ensure reliable reference data, uncontaminated cloud and clear-sky pixels were manually extracted from all dust and additional non-dust scenes. For pixel selection, individual pixels were assigned to one of the following categories: dust, cloud, clear-sky ocean, sunglint, volcanic ash, smoke, or ice/snow surface. For the purpose of training the Random Forest (RF) model, these classes were consolidated into two groups: dust and non-dust.

A check to ensure a good representation of regions most impacted by dust is illustrated in Figure 2 (a), which shows the global distribution of the selected pixels and can be compared to the global dust AOT by Kok et al. (2021). The dust training dataset



**Table 1.** Central wavelengths of MSI and MODIS spectral bands in  $\mu\text{m}$

| Channel | MSI   | MODIS |
|---------|-------|-------|
| VIS     | 0.67  | 0.659 |
| NIR     | 0.865 | 0.865 |
| SWIR-1  | 1.65  | 1.64  |
| SWIR-2  | 2.21  | 2.13  |
| TIR-1   | 8.8   | 8.55  |
| TIR-2   | 10.8  | 11.03 |
| TIR-3   | 12.0  | 12.02 |

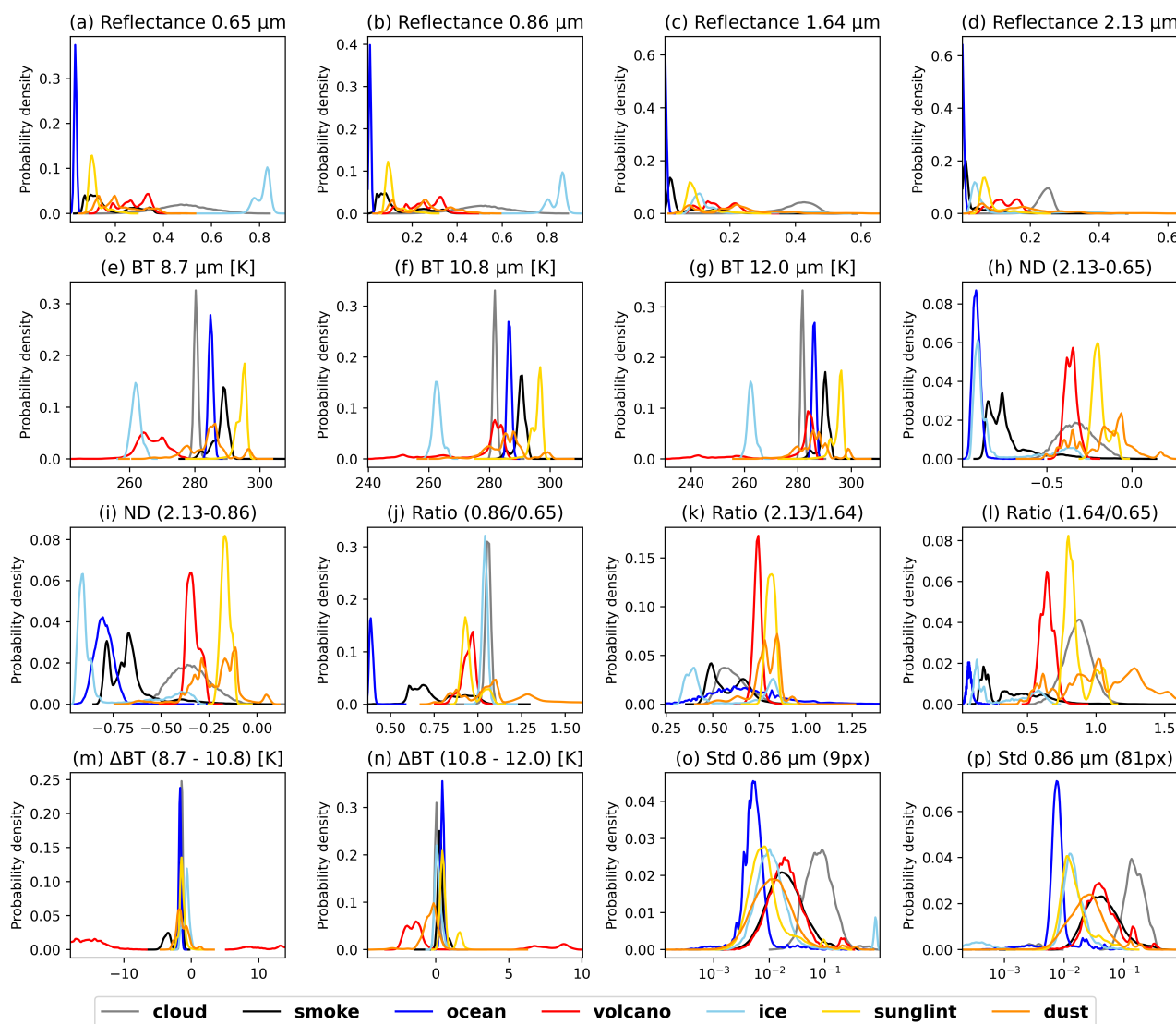


**Figure 2.** Dust pixel (a) and non-dust pixel (b) overview: The locations of selected pixels. The counts of dust pixel over the North Atlantic, Mediterranean, Red Sea, Arabian Sea, and Yellow Sea are primarily from the year 2021. Additional cases, representing less frequent dust regions, span from 2003 to 2024.

includes over one million pixels, accounting for approximately 10 % of the total training pixels. The remaining pixels represent non-dust pixels, including ocean, clouds, and other types of aerosols. The ratio of dust to non-dust samples of this study is similar to that used by Lee et al. (2021). Even though it is low with dust clearly being the minority class, it is still significantly higher than globally averaged as dust plumes are relatively rare. Dalponte et al. (2012) cautions that using imbalanced datasets can lead to biased results and Mellor et al. (2015) reports that balanced datasets often yield the best accuracy. However, they also note that some level of imbalance can be strategically advantageous, as it can help to improve the detection of rare classes without significantly compromising the overall classification performance.

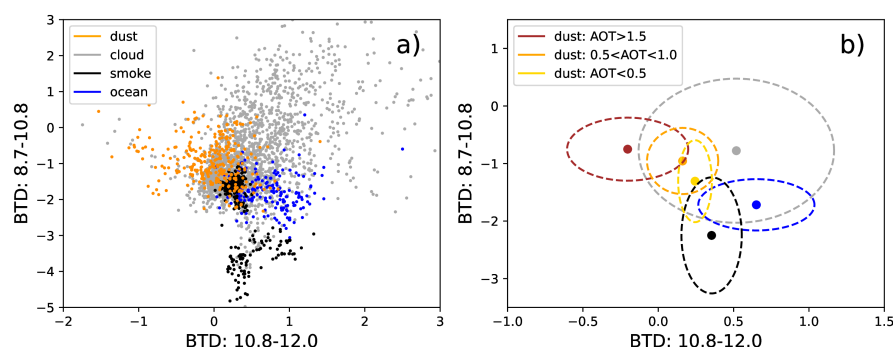
## 2.2 Initial feature selection

Data from spectrometers, which can include variables such as single-channel information, spectral tests, coordinates, and solar and observation geometries, are used as input for RF models and other machine learning methods. In machine learning, these inputs are commonly referred to as features.



**Figure 3.** PDFs of reflectances (a-d), brightness temperatures (e-g) as well as spectral and spatial tests, including normalized differences (ND) of reflectance (h) and (i), reflectance ratios (j-l), BTDs (m) and (n) and NIR standard deviation of 9 (o) and 81 (p) pixels, respectively.

Probability density functions (PDFs) were employed in Figure 3 to characterize the dataset and to investigate the relative likelihood distributions of reflectances and brightness temperatures among the considered categories. In addition, several potential spectral tests for the MSI channels were evaluated with respect to their capability to discriminate dust from other atmospheric and surface constituents. This approach was motivated by the work of Zhou et al. (2020), who utilized PDFs of MODIS-  
95 based spectral tests to derive threshold values for a dust detection algorithm. In the present study, however, manually defining thresholds is unnecessary, as the RF classifier determines optimal decision boundaries autonomously. Nevertheless, the PDFs



**Figure 4.** Detailed brightness temperature differences overview for dust, cloud, ocean and smoke: BTDs scatter plot of randomly selected pixels from dust, cloud, ocean, and smoke datasets in (a). In (b), points are the arithmetic mean of the categories. The ellipses are the standard deviations of the BTDs. Dust was separated in three AOT sections to evaluate the impact of layer thickness.

remain valuable, as they provide insight into the spectral behavior of the investigated categories and atmospheric constituents. Furthermore, the inclusion of spectral tests as input features may facilitate more effective decision-tree splits within the RF model and thereby improve classification performance (Berndt et al., 2021). It is therefore examined subsequently whether the inclusion of spectral tests yields a measurable improvement or whether the RF model can achieve comparable performance using the original channel information alone (see Sec. 3). Figure 3 (e-g) illustrates the PDFs of the brightness temperatures for the three TIR channels. The distributions indicate that single-channel TIR tests alone are insufficient for reliable discrimination, as substantial overlap exists between the different categories. Consequently, these channels provide only limited utility for pixel-wise classification. Zhou et al. (2020) proposed the use of the 8.7–10.8  $\mu\text{m}$  brightness temperature difference (BTB) for distinguishing volcanic plumes from dust. This approach is effective because strong  $\text{SO}_2$  absorption within the 8.7  $\mu\text{m}$  channel produces distinctly low BTB values, as also reflected in the PDFs presented here (Li et al., 2022). However, the present dataset includes observations of the 2020 Hunga Tonga eruption, an exceptional event characterized by extremely high water vapor concentrations and unusually low  $\text{SO}_2$  abundance. As a result, the associated BTB signatures differ substantially from those typically observed for volcanic plumes (Vömel et al., 2022). Cases with enhanced water vapor content, though less extreme than Hunga Tonga, may therefore produce BTB values that overlap with the dust regime. Similarly to single BTs, the BTBs shown in Figure 3 (m), (n) do not achieve a satisfactory separation. In particular, the enhanced absorption by dust at 10.8  $\mu\text{m}$  is not distinctly identifiable, leading to considerable overlap with ocean, cloud, and smoke pixels. A more detailed representation is provided in Figure 4 a), where both BTBs are used as coordinate axes. Although a substantial fraction of cloud pixels, particularly ice clouds (not highlighted separately from liquid clouds here), can be distinguished from dust using the 10.8–12.0  $\mu\text{m}$  BTB, with many cloud pixels exhibiting values above 1 while dust remains below 1, a considerable number of cloud pixels still display BTB characteristics similar to dust. Figure 4 (b) further subdivides the dust dataset according to aerosol optical thickness (AOT), distinguishing between thin dust ( $\text{AOT} < 0.5$ ), moderate dust ( $0.5 \leq \text{AOT} < 1.0$ ), and thick dust ( $\text{AOT} > 1.5$ ). The points represent arithmetic means, whereas the ellipses denote the corresponding standard deviations



for both BTDs. Increasing dust optical thickness improves the separation from clouds; however, ambiguities between dust and cloud pixels remain evident.

Figure 3 (a-d) presents the PDFs of the reflectances for the four VNS channels. In general, reflectance increases with increasing dust optical thickness. For low AOT conditions, the dust signal in the  $0.65\ \mu\text{m}$  and  $0.86\ \mu\text{m}$  channels overlaps with the more absorptive smoke, while volcanic ash exhibits reflectances comparable to those of optically thicker dust across all VNS channels. Consequently, discrimination between aerosol types based solely on single-channel reflectance information is challenging. Clouds generally exhibit substantially higher reflectances than dust across all channels. However, optically thin clouds overlap with the reflectance range of dust, preventing an unambiguous separation. In addition, sunglint substantially enhances the reflectance of clear-sky ocean pixels, producing values comparable to those observed for dusty scenes. To extract even more information from the available VNS channels, several spectral tests compatible with MSI capabilities were investigated with the most promising tests shown in Figure 3 (h-l). Figures 3 (h) and (i) present spectral tests inspired by the NDDI concept. These tests compute normalized differences between the SWIR channel at  $2.13\ \mu\text{m}$  and the VIS and NIR channels at  $0.65\ \mu\text{m}$  and  $0.86\ \mu\text{m}$ , respectively. The underlying rationale is that dust reflectances remain comparatively constant across the VNS spectrum, whereas the reflectances of clouds and smoke decrease with increasing wavelength. While smoke can be separated reasonably well, volcanic aerosol overlaps almost entirely with dust, and clouds can only be distinguished under conditions of exceptionally thick dust that produce very large normalized differences. Furthermore, sunglint values overlap with those associated with very thick dust layers, emphasizing the necessity of explicitly masking sunglint regions in the dust detection procedure. Hence, sunglint pixels were subsequently excluded from the training dataset due to their high spectral similarity to dust, which could lead to classification ambiguities. Consequently, the dust detection algorithm is not applicable to sunglint-affected regions. However, the impact of this limitation is minimal, as sunglint areas are relatively small owing to MSI's swath tilt. Additionally, ratio-based tests were investigated, as illustrated in Fig. 3 (j-l). In contrast to normalized differences, these ratios provide improved discrimination between dust and clouds. Nevertheless, substantial overlap with volcanic aerosol and sunglint conditions remains evident.

In addition to the brightness temperatures, brightness temperature differences, reflectances, solar and satellite observation angles, the 9 or 81-pixel standard deviation of the NIR reflectance was also included in the data to test spatial variability as shown in Figure 3 (e) and (p). Those tests exploit the greater spatial homogeneity of dust layers compared to clouds and is used to discriminate between the two classes. The encouraging performance of spatial variability tests, shown by the low overlap between dust and cloud, is in close agreement with the findings of Darmanov and Sokolik (2009).

Overall, the PDFs demonstrate that a clear bimodal separation between dust and non-dust classes is not achievable. Compared with the PDFs presented by Zhou et al. (2020), the exclusive spectral range occupied by dust is substantially smaller in the MSI-based tests, rendering the manual definition of threshold values impractical. Given the extensive overlap between classes revealed by the PDF analysis, it can therefore be concluded that more sophisticated machine learning approaches are required to achieve an accurate MSI-based dust classification.

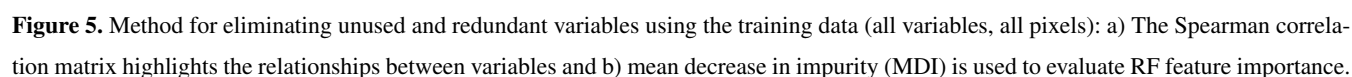


### 3 Method

The concept of RF is to randomly create multiple decision trees, each of which generates its own prediction (Breiman, 2001) using random sampling. The final prediction for a data point is made by summarizing the predictions of all trees by averaging for regression tasks or majority voting for classification tasks. For creating a dust mask, the RF tool of the python machine learning tool scikit-learn was used (Pedregosa et al., 2011). In the first setting, the RF model used the following dataset features as described in the previous section:

- based on single channels:
  - Reflectances at  $0.65\ \mu m$ ,  $0.86\ \mu m$ ,  $1.64\ \mu m$ ,  $2.13\ \mu m$
  - Brightness temperatures at  $8.7\ \mu m$ ,  $10.8\ \mu m$ ,  $12.0\ \mu m$
- based on spectral tests:
  - Normalized differences between:
    - $2.13\ \mu m$  and  $0.65\ \mu m$
    - $2.13\ \mu m$  and  $0.86\ \mu m$
  - Reflectance ratios between:
    - $0.86\ \mu m$  and  $0.65\ \mu m$
    - $2.13\ \mu m$  and  $1.64\ \mu m$
    - $1.64\ \mu m$  and  $0.65\ \mu m$
  - Brightness temperature differences between:
    - $8.7\ \mu m$  and  $10.8\ \mu m$
    - $10.8\ \mu m$  and  $12.0\ \mu m$
- based on spatial tests:
  - spatial variability:
    - 9-pixel standard deviation ( $0.86\ \mu m$ )
    - 81-pixel standard deviation ( $0.86\ \mu m$ )

To simplify the model, the features in the dataset were analyzed for their correlation and importance. The concept is to identify highly correlated variables and then shorten the model by choosing the one that is more important for the model. Figure 5 provides an overview of this assessment. First, Spearman correlation (Figure 5 (a)) was calculated, which compares the ranks of the variables within the dataset rather than their actual values, making it well-suited for identifying non-linear relationships. The observed correlations are expected. Over ocean, the reflectances typically increase with higher optical thickness, while brightness temperatures generally decrease when absorbers are located in higher layers. Additionally, since spectral tests contain information from individual channels, these channels are inherently correlated.



Single-channel brightness temperatures ranked low in importance as they do not capture the spectral signal of dust. Therefore, brightness temperatures were not considered in the reduced feature set. BTD 8.7-10.8  $\mu m$ , although uncorrelated, has low importance but might potentially compensate for the exclusion of single channels brightness temperatures. Both spatial tests were considered important. Since they are inherently correlated, one test could be sufficient and only the 9-pixel standard deviation was retained in the reduced set of features. Additional reflectances at 0.65  $\mu m$  and the normalized reflectances at 2.13 and 0.65  $\mu m$  were omitted due to their lower importance compared to their highly correlated counterparts. It can be concluded that spectral tests have slightly improved the model, whereas the spatial test based on the standard deviation is considered indispensable. The 9-pixel standard deviation achieved the highest importance, further supporting the recommendation of Darmenov and Sokolik (2009) to use spatial tests for dust detection. Compared to other RF dust detections (e.g., Lee et al., 2021; Georganos et al., 2018), this is the only one that makes use of this approach so far. In the case of MODIS dust detection, the



195 spatial variability test serves only to exclude pixels with extreme variability, but not necessarily to favor a dust classification for homogeneous layers. In addition, BTDs of  $10.8 - 12.0 \mu m$  prove to be decisive information from the TIR range that confirm premises by Ackerman (1997). Additionally, a statistical analysis was performed by calculating the probability of correct detection (POCD), and the probability of false detection (POFD). In this context, "positive" refers to dust, and "negative" refers to non-dust.

$$200 \quad POCD = \frac{\text{true positive}}{\text{true positive} + \text{false negative}} \quad (1)$$

$$POFD = \frac{\text{false positive}}{\text{true negative} + \text{false positive}} \quad (2)$$

Thus, the accuracies for dust (POCD) and non-dust ( $1 - POFD$ ) are calculated on separate datasets and the overall accuracy as well as other statistical parameters relating to the entire dataset are omitted. One reason for this is that the dataset would  
205 overrepresent dust as it does not account for the actual global proportion of dust pixels, which is unknown and estimated to be very low on a global scale.

Consequently, it is crucial for the model to achieve a particularly low POFD as otherwise, the ratio of false dust to true dust pixels would be excessively high when applied to larger datasets and not only to dust cases. Allowing for a high probability of false positive values, the non-dust test dataset contains a particularly large number of cases that are difficult to classify  
210 (volcano, cloud over dust and thin clouds).

**Table 2.** Sensitivity of model accuracy to selected features

| Model number | Model features              | POCD  | POFD  |
|--------------|-----------------------------|-------|-------|
| M1           | Subset                      | 88.09 | 0.028 |
| M2           | All                         | 83.97 | 0.056 |
| M3           | Single channels + 9-pxl-std | 87.59 | 0.057 |
| M4           | Single channels             | 5.62  | 0.053 |
| M5           | Spectral tests + 9-pxl-std  | 71.37 | 0.037 |
| M6           | Spectral tests              | 57.23 | 0.185 |

Table 2 summarizes the POCD and POFD evaluated for several RF model feature settings. Model M2 uses all 23 features of the dataset, while Model M1 employs the reduced set of features identified as important after excluding unnecessary ones using Fig. 5. Models M3 to M6 represent additional configurations, each developed by selectively excluding sets of features, such as single-channel reflectances, brightness temperatures, spatial tests, or spectral tests in various combinations. Compared  
215 to the full variable model M2, the reduced variables model M1 performed better.



Consequently, the model with reduced features (M1), including the spectral tests, a spatial test and the single channel data, was considered to be the most effective. Hence, the final setting of the RF model was as follows. The final set of used features includes:

- based on single channels:

220       – Reflectances at  $0.86 \mu m$ ,  $1.64 \mu m$ ,  $2.13 \mu m$

- based on spectral tests:

- Normalized differences between  $2.13 \mu m$  and  $0.86 \mu m$

- Reflectance ratios between:

0.86  $\mu m$  and 0.65  $\mu m$

225       2.13  $\mu m$  and 1.64  $\mu m$

1.64  $\mu m$  and 0.65  $\mu m$

- Brightness temperature differences between:

8.7  $\mu m$  and 10.8  $\mu m$

10.8  $\mu m$  and 12.0  $\mu m$

230       – based on spatial tests:

- spatial variability: 9-pixel standard deviation ( $0.86 \mu m$ )

Additional sensitivity studies (not shown) lead to the most effective configuration of the RF model. The number of trees was set to 100, the tree depth to ten and the number of maximum features for splitting was set to three. The objective is to reliably  
235 detect dust layers that lead to cloud misclassifications rather than finding thin dust layers. Therefore, a minimum MODIS AOT of 0.7 in the dust pixel training data was used to exclude optically thin dust layers, as they otherwise lead to more ambiguity and ultimately to a higher POFD. The sensitivity can similarly be controlled with the RF probability threshold, defined here as the fraction of positively voting trees required for an overall dust classification. The RF threshold was kept at 50%, while a higher value could be applied even after training if more robustness is required.

#### 240   4   Application to MSI

In the following, the final dust detection model was applied to two MSI scenes with colocated MODIS Aqua overpasses to assess the model on both imagers. One scene having a thick dust layer ( $AOD > 1$ ) and a second scene with a thin dust layer ( $AOD < 1$ ). The RF dust detection was compared with the dust flag from the MODIS cloud mask (MYD35) (Zhao et al., 2010). The operational MODIS dust flag uses eight channels for daytime operation over ocean, including the same spatial variability  
245 test from this study. Both scenes reveal misclassifications by the operational MSI cloud mask and are therefore evaluated for



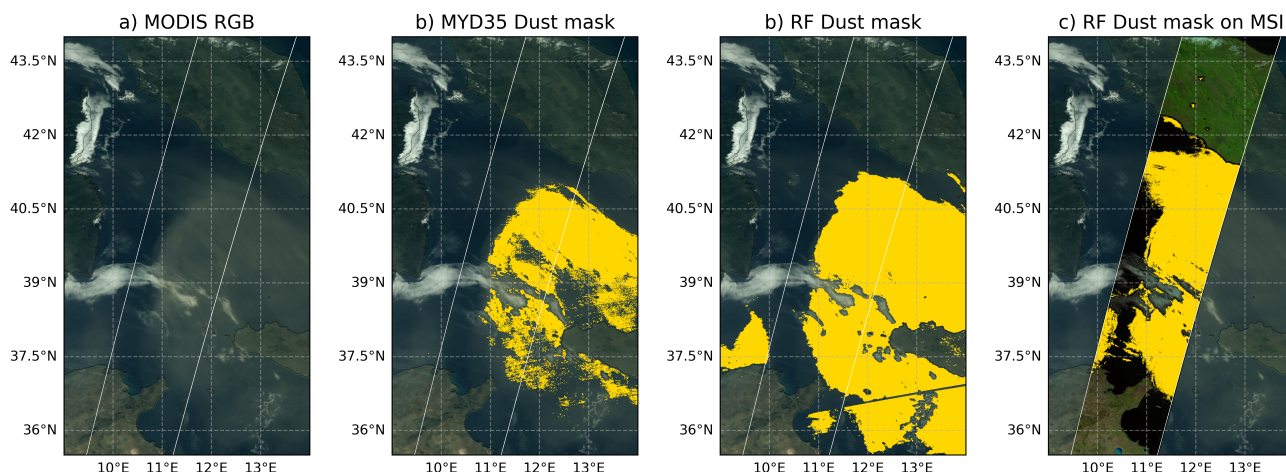
their potential to improve classification by adding a dust class.

Fig. 6 demonstrates the performance of the RF-based dust mask using a first test case. It shows a MODIS image excerpt starting over Italy, crossing the Mediterranean Sea, and ending over Tunisia. A thick dust plume over the Mediterranean, as shown in Fig. 6 (a), partly overlaps with clouds. The MODIS dust mask shown in Fig. 6 (b) avoids cloudy pixel and only the thickest parts of the dust plume are classified as dust. However, the RGB (Fig. 6 (a)) indicates more dusty pixels, which the RF dust mask in panel (c) detects, while still avoiding cloud pixels that are clearly identifiable by eye. Nonetheless, clouds below the dust layer might be missed. Fig. 6 (d) shows the same scene with the MSI false-color image overlaid, which was taken 50 minutes later. It shows a comparable dust detection to the MODIS-based scene. The RF algorithm can be applied to both imagers, MODIS and MSI, and finds a similar number of dusty pixels. It yields 53.26% dusty pixels when applied to MODIS data within the MSI swath and 50.74% when directly applied to MSI data.

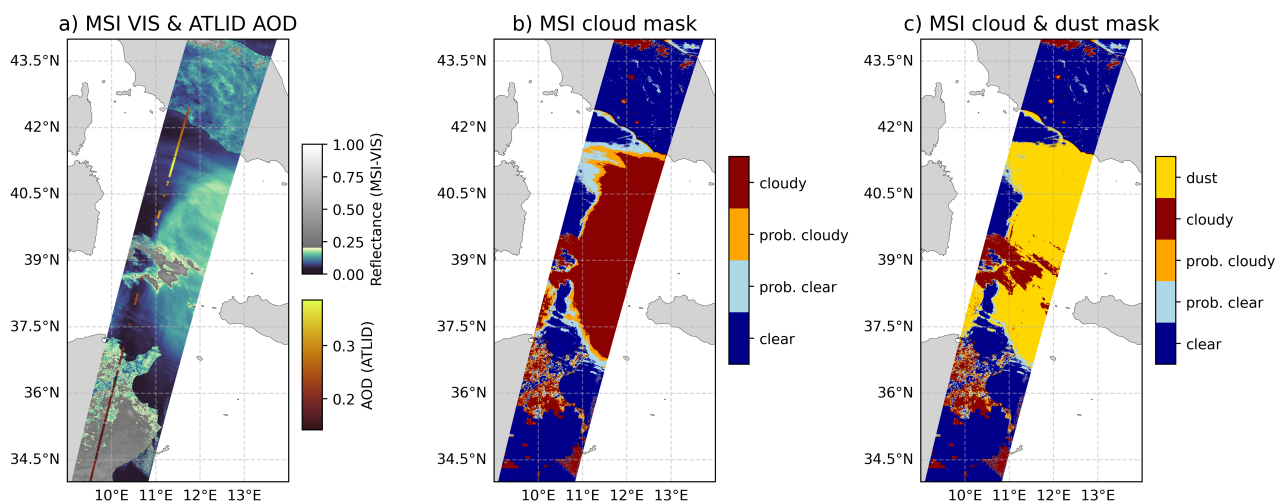
Fig. 7 shows the corresponding EarthCARE-only perspective and highlights the potential performance improvement for the operational MSI cloud mask. Fig. 7 (a) highlights the visible reflectance from MSI in an aerosol range to focus on the dust layer. Here, the desert in the south and brighter clouds are depicted in gray scale. Regardless, thin clouds can also be in the low reflectance range. In addition, ATLID also shows increasing AOD while overpassing thinner parts of the same dust layer, although, the thick part of the plume is unfortunately not observed. Finally, 7 (c) demonstrates the potential future improvement of the MSI cloud mask. While the operational MSI cloud mask (b) classifies thick dust as cloudy and thinner clouds as *probably clear* or *probably cloudy*, the new dust class (c) keeps clouds over dust as *confident cloudy* and reclassifies pixels from the plume to dust.

In a second case (Fig. 8), the performance of the RF-based dust mask is evaluated for a thin dust layer over the Atlantic between the Cape Verde Islands and the African mainland. The layer is confirmed by e.g., the ACTRIS (Aerosol, Clouds, and Trace Gases Research Infrastructure; (Laj et al., 2024)) facility located at the Ocean Science Center Mindelo (OSCM) and the Deep Blue aerosol typing product retrieved from VIIRS data (Hsu et al., 2019). The MYD35 dust flag is not detecting the dust layer (not shown). The RF model has been applied to MODIS and MSI data and detects it (see Fig. 8). Again, the RF dust mask shows a similar performance when applied to MODIS and MSI data (observed 20 minutes apart) within the MSI swath, detecting 34.17% and 42.25%, respectively.

Fig. 9 (a) shows that an increase in reflectance of the dust plume correlates with an increase in AOD by ATLID. Within the dust plume, the operational M-CM product has 54% of pixels classified as *probably clear* or *probably cloudy*. The RF-based dust mask reclassifies almost all pixel to dusty, leading to only 16.64% of the pixels to remain in one of the probably categories in Fig. 9(c). However, the western part of this scene remains *confident clear*. This is attributed to the lower AOD threshold ( $AOD > 0.8$ ) used during training of the RF-based dust model and does not imply an absence of dust. Nonetheless, within the operational MSI chaining framework, this is sufficient, since the subsequent MSI aerosol algorithm uses confident clear pixels by default anyway and would add pixels classified as dust to its retrieval leading to an improved coverage of AOD.



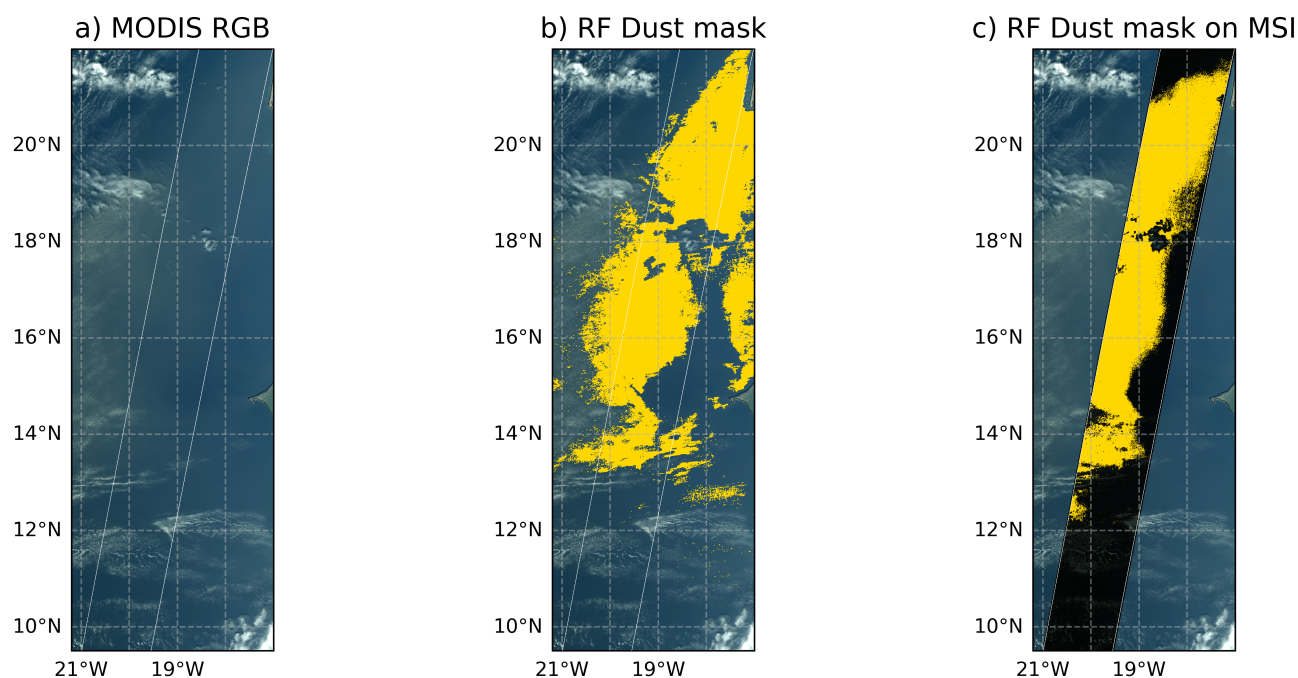
**Figure 6.** Aqua MODIS detection of a thick dust plume over the Mediterranean on 15 October 2024 at 12:50 UTC. All panels show the true-color RGB along with the MSI swath edges, indicated by white lines from the EarthCARE overpass at 13:40 UTC from frame 02172D. Panel b) features the Suspended dust flag from the MYD35 product. Panel c) and d) show the RF dust mask, applied on MODIS and MSI, respectively. For panel d), a false-color RGB from MSI is used as background.



**Figure 7.** Panel a) shows the dust plume from frame 02172D as observed by the MSI-VIS channel with focus on low reflectance for display of aerosols. The AOD derived from ATLID (A-EBD and A-TC) is plotted along the satellite track. The MSI cloud mask from M-CM is presented in b), with c) showing an updated version that features the RF dust mask as additional class.

## 280 5 Conclusions

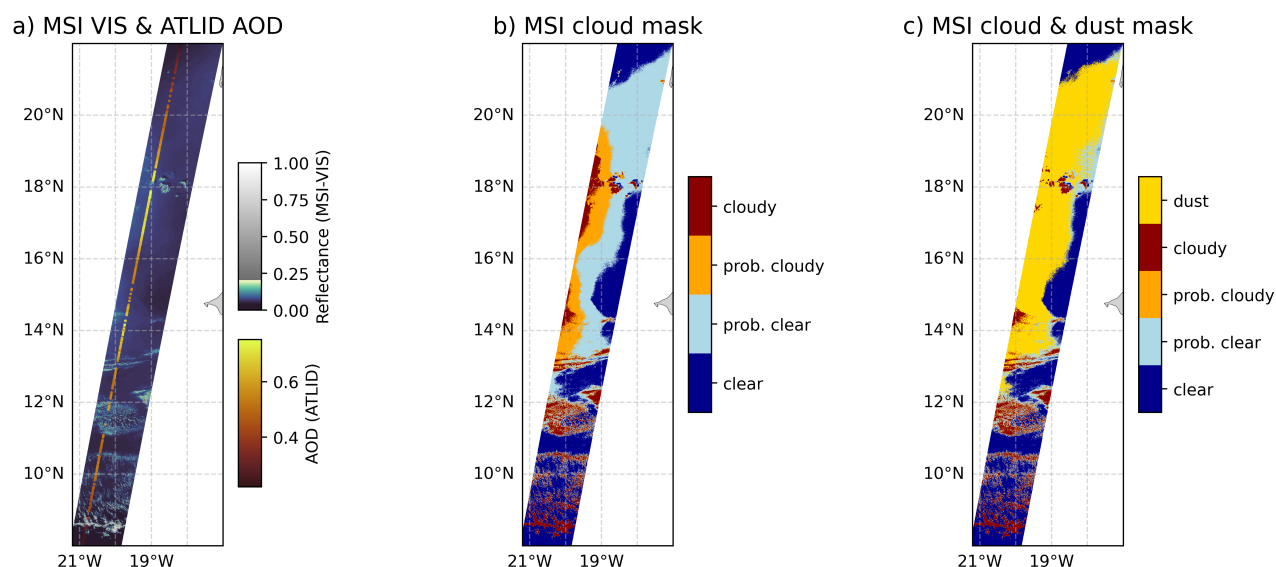
This study introduces a promising dust detection algorithm for MSI onboard EarthCARE, aimed at enhancing the operational cloud mask product accuracy. By successfully identifying and distinguishing between clouds and dust aerosols over the ocean,



**Figure 8.** Aqua MODIS detection of a thin dust plume over the Atlantic between the Cape Verde Islands and the African mainland on 22 October 2024 at 15:45 UTC. All panels show the true-color RGB along with the MSI swath edges, indicated by white lines from the EarthCARE overpass at 15:25 UTC from frame 02282E. Panel b) and c) show the RF dust mask, applied on MODIS and MSI, respectively. For panel c), a false-color RGB from MSI is used as background.

the developed RF model overcomes a critical limitation of the current MSI cloud mask algorithm, which misclassifies thick aerosol layers as clouds. The approach capitalizes on the reduced spectral information available from MSI, leveraging four solar, three thermal channels and the spatial variability to capture the characteristic optical and thermal properties of dust. In particular, the recovery of misclassified dust pixel as cloud looks promising. The model, tuned to achieve an optimal balance of sensitivity and precision, demonstrated its capability in detecting dust pixels with good detection performance (minimum AOT threshold of 0.7 and a minimum dust probability of 0.5), improving upon comparable methods (e.g., case 2 presented in this study (Ackerman, 2015)).

However, to fully optimize this approach for operational use, several considerations and next steps are necessary. Notably, the spectral response of MSI, particularly in the TIR, necessitates adjustments and therefore, justify the need for a MSI-based training data set. Further, the synergistic potential of EarthCARE's multi-instrument approach—combining MSI with ATLID, among others—provides a unique opportunity for further refinement. Utilizing co-located measurements from ATLID, which offers precise aerosol optical thickness and aerosol typing (Donovan et al., 2024), could significantly enhance the dust detection accuracy. A new, dedicated dataset leveraging MSI and ATLID observations would be ideal for this purpose. In addition, the



**Figure 9.** Dust plume as detected by EarthCARE frame 02282E with same layout as used in Fig. 7.

spatial variability test could be adjusted to ensure an optimal performance for MSI's 500x500 m pixel resolution, compared to MODIS 1x1 km resolution. This could then potentially alter number of pixel used for the calculation of the standard deviation.

The successful proof-of-concept established by this work highlights the viability of machine learning approaches, particularly RF classification, for addressing the complexities of multi-spectral data and the importance of integrating spatial context into detection algorithms. Further, work towards operational implementation will not only improve the accuracy and coverage of cloud and aerosol products from EarthCARE but also contribute to advancing the broader field of dust detection and aerosol remote sensing.

*Data availability.* Training and test data set can be made available upon request.

*Author contributions.* All authors have contributed to this work. GW, AH and ND conceptualized the work. GW created the training and test datasets and implemented the RF model. GW created all figures. GW, ND and AH wrote the manuscript together. SB and NM supported the work and revised the initial manuscript.

*Competing interests.* The authors declare that they have no conflict of interest.



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