

1 **”Seeing” beneath the clouds - machine-learning-based**
2 **reconstruction of North African dust events**

3 **Franz Kanngießer^{1*} and Stephanie Fiedler^{1†}**

4 ¹Institute of Geophysics and Meteorology, University of Cologne, DE-50923 Cologne, Germany

5 **Key Points:**

- 6 • We present the first fast reconstruction of cloud-obscured Saharan dust plumes
7 through novel machine learning applied to satellite images.
8 • Up to 15% of all observations by classical satellite images may miss cloud events
9 compared to reconstructed dust plumes.
10 • WMO dust forecasts for North Africa mostly agree with the satellite-based recon-
11 struction of the dust plume extent.

*now: GEOMAR Helmholtz Center for Ocean Research Kiel, DE-24105 Kiel, Germany

†now: GEOMAR Helmholtz Center for Ocean Research Kiel, DE-24105 Kiel, Germany and Christian-Albrechts University of Kiel, DE-24118 Kiel, Germany

Corresponding author: Franz Kanngießer, fkangiesser@geomar.de

Abstract

Mineral dust is one of the most abundant atmospheric aerosol species and has various far-reaching effects on the climate system and adverse impacts on air quality. Satellite observations can provide spatio-temporal information on dust emission and transport pathways. However, satellite observations of dust plumes are frequently obscured by clouds. We use a method based on established, machine-learning-based image in-painting techniques to restore the spatial extent of dust plumes for the first time. We train an artificial neural net (ANN) on modern reanalysis data paired with satellite-derived cloud masks. The trained ANN is applied to gray-scaled and cloud-masked false-color daytime images for dust aerosols from 2021 and 2022, obtained from the SEVIRI instrument onboard the Meteosat Second Generation satellite. We find up to 15 % of summertime observations in West Africa and 10 % of summertime observations in Nubia by satellite images miss dust events due to cloud cover. The diurnal and seasonal patterns in the reconstructed dust occurrence frequency are consistent with known dust emission and transport processes. We use the new dust-plume data to validate the operational forecasts provided by the WMO Dust Regional Center in Barcelona from a novel perspective. The comparison elucidates often similar dust plume patterns in the forecasts and the satellite-based reconstruction, but the latter computation is substantially faster. Our proposed reconstruction provides a new opportunity for validating dust aerosol transport in numerical weather models and Earth system models. It can be adapted to other aerosol species and trace gases.

Plain Language Summary

Most dust and sand particles in the atmosphere originate from North Africa. Since ground-based observations of dust events in North Africa are sparse, investigations often rely on satellite observations. Dust events are frequently obscured by clouds, making it difficult to study the full extent. We use machine-learning methods to restore the full extent of dust events in 2021 and 2022 at 9, 12, and 15 UTC. Our analysis focuses on the reconstructions at 12 UTC. The spatial patterns of the restored dust events are compared to earlier work using satellite observations of dust and known atmospheric processes driving the emission and transport of dust. We use the reconstructed dust patterns to validate the dust forecast ensemble provided by the WMO Dust Regional Center in Barcelona, Spain. Our proposed method is computationally inexpensive and provides new opportunities for assessing the quality of dust transport simulations. The method can be transferred to reconstruct other aerosol and trace gas plumes.

1 Introduction

Mineral dust constitutes one of the major aerosol types in the atmosphere by mass fraction (Pósfai & Buseck, 2010). It has profound direct and indirect effects in the Earth system, e.g. by directly affecting atmospheric radiative transfer, by acting as cloud condensation and ice nuclei, and by providing nutrients to terrestrial and marine ecosystems, including the fertilization of the Amazon rainforest by North African dust (e.g., Talbot et al., 1986; Swap et al., 1992; Buseck & Pósfai, 1999; Griffin & Kellogg, 2004; Goudie, 2009; Hoose et al., 2010; P. Seifert et al., 2010; Pósfai & Buseck, 2010; Bristow et al., 2010; Mahowald et al., 2017; Kok et al., 2023). Furthermore, North African dust can be linked to Hurricane activity in the North Atlantic (Evan et al., 2006; Strong et al., 2018). Mineral dust also provides surfaces for chemical reactions and can, thus, act as a sink for certain chemical compounds (Buseck & Pósfai, 1999; Pósfai & Buseck, 2010). In addition to these effects, dust storms have multi-faceted impacts, including disruption of public services, public events, economic activity, and air traffic, as well as reducing photovoltaic energy production, adversely impacting public health, and diminishing agricultural yields (Monteiro et al., 2022; Al-Hemoud et al., 2017; Goudie, 2014; N. Middle-

ton, 2017; Stefanski & Sivakumar, 2009). In addition to reduced air quality by particulate matter, adverse public health impacts also stem from the co-emission of micro-organisms, bacteria, fungi, and viruses with dust particles (Griffin, 2007). While Europe itself lacks large source regions of mineral dust, dust transported to Europe is specifically linked to both adverse impacts on human health, disruption of transport and public services, and also linked to an enhanced melting of Alpine glaciers when the dust is deposited (Q. Wang et al., 2020; Karanasiou et al., 2012; Oerlemans et al., 2009; Gabbi et al., 2015; Di Mauro et al., 2019; Monteiro et al., 2022).

North Africa is by far the largest source region of mineral dust (Tanaka & Chiba, 2006; Huneus et al., 2011; Kok et al., 2021, 2023). Due to the sparse ground-based observations in Northern Africa studying emissions of Saharan dust strongly relies on satellite observations. Dust emission and transport processes are frequently linked with the presence of clouds (e.g., Heinold et al., 2013; Ben-Ami et al., 2009; Bou Karam et al., 2010; Knippertz & Todd, 2012; Allen et al., 2013; Roberts & Knippertz, 2014; Bou Karam et al., 2014; Fromm et al., 2016). Consequently, the full spatial extent of dust plumes as observed by satellite-borne instruments is often obscured by clouds. In this study, we propose to resolve the shortcoming with a novel machine-learning-based reconstruction of North African dust events, which employs image in-painting techniques.

Geostationary satellites can provide observations with high temporal resolution. One sensor facilitating this is the Spinning Enhanced Visible and Infrared Imager (SEVIRI), a passive radiometer and the primary instrument onboard the Meteosat Second Generation (MSG) satellites (Schmetz et al., 2002). SEVIRI provides measurements of radiance from 12 different spectral channels and one broadband channel every 15 minutes. The spectral channels are centered around wavelengths between $\lambda = 0.635 \mu\text{m}$ and $\lambda = 13.40 \mu\text{m}$. By combining the information from different instrument channels false-color RGB images are created. In RGB color spaces each color can be decomposed into red (R), green (G), and blue (B) components. On these RGB images various atmospheric features, such as different cloud types, air masses, trace gases like SO_2 , volcanic ash, and mineral dust can be identified. The RGB product, on which dust features are shown in bright magenta, the Dust RGB, assigns (differences of) brightness temperatures from three infrared bands, specifically $\lambda = 8.7 \mu\text{m}$, $10.8 \mu\text{m}$, and $\lambda = 12.0 \mu\text{m}$, to the images' red, green, and blue channels (Schepanski et al., 2007; Lensky & Rosenfeld, 2008; Banks et al., 2019). This product has been used for studies of dust emission frequencies and transport pathways (e.g., Schepanski et al. (2007, 2012); Ashpole and Washington (2012); Trzeciak et al. (2017); Allen et al. (2013); Bou Karam et al. (2010, 2014); H. Yu et al. (2021); Dhital et al. (2020); Solomos et al. (2017)) with the caveat that dust beneath clouds is not visible.

No attempt to resolve the cloud-masking of dust plumes in satellite images has been made to date, but approaches for other cloud-obscured features have been successfully tested. These features were often stationary and often subject to only small temporal changes, such as land cover information (Chauhan et al., 2021; Chen et al., 2020; Czerkawski et al., 2022; Enomoto et al., 2017; Li et al., 2020; L. Liu & Hu, 2021; Pan, 2020; Sarukkai et al., 2020; Singh & Komodakis, 2018; M. Zhao et al., 2021; Zi et al., 2022). Further examples are for land-surface temperature (W. Zhao & Duan, 2020; Sarafanov et al., 2020; Weiss et al., 2014), evapotranspiration (Cui et al., 2020), sea-surface temperature (Dong et al., 2019), and chlorophyll a (Stock et al., 2020).

A substantial amount of dust emissions and consequently transport might be obscured by clouds. Convection-permitting simulations over West Africa indicate a diurnal cycle of dust emission coinciding with cloud cover in summertime West Africa. Between $\sim 6\%$ (19:00 local time) and up to 55% (10:00 local time) of dust emissions in West Africa occur during clear sky conditions in the simulation (Heinold et al., 2013). Unlike cloud-obscured features like land cover and chlorophyll a, dust storms as well as clouds co-develop in time and space. Dust emission in Northern Africa is frequently linked to

115 outflows from mesoscale convective systems during summer (Allen et al., 2013; Heinold
 116 et al., 2013; Allen & Washington, 2014; Roberts & Knippertz, 2014; Bou Karam et al.,
 117 2014). A significant amount of North African dust transported over the North Atlantic
 118 is above and within the marine boundary layer and interacts with stratiform clouds (Ben-
 119 Ami et al., 2009). Baroclinic storms are another mechanisms for long-distance dust trans-
 120 port, which is associated with clouds (Schepanski & Knippertz, 2011; Fiedler et al., 2014;
 121 Fromm et al., 2016).

122 In this study we employ an artificial neural network (ANN) to reconstruct the full
 123 extent of partially obscured North African dust events. This type of ANN was previously
 124 used to reconstruct historical temperature anomalies (Kadow et al., 2020). The ANN
 125 is trained on cloud-masked reanalysis data of the aerosol optical depth, provided by the
 126 Copernicus Atmosphere Monitoring Service (CAMS) (Inness et al., 2019b). The trained
 127 ANN is then used to reconstruct the below-cloud extent of dust events by applying it
 128 to gray-scaled and cloud-masked images based on the MSG-SEVIRI Dust RGB prod-
 129 uct. These reconstructions are used to compute the dust occurrence frequency as annual
 130 mean and as mean seasonal patterns at 9, 12, and 15 UTC with a particular focus on
 131 12 UTC. The reconstructions are then used to evaluate spatial patterns of dust plumes
 132 in operational dust forecasts, which are used by the WMO for warnings, with complete
 133 spatial information of the dust plume based on satellite data.

134 2 Methods and Data

135 2.1 Datasets

136 2.1.1 Satellite datasets

137 We propose and test a machine-learning-based reconstruction of dust events in North
 138 Africa. More specifically, we reconstruct cloud-masked, gray-scaled images of EUMET-
 139 SAT’s Dust RGB product (EUMETSAT, 2009b). The Dust RGB images are obtained
 140 by assigning to each of the RGB channels, a different combination of brightness temper-
 141 ature observations, T_B , from different SEVIRI infra-red channels as follows (Lensky &
 142 Rosenfeld, 2008):

$$143 R = \frac{T_{B,12.0\mu\text{m}} - T_{B,10.8\mu\text{m}} + 4 K}{6 K} \quad (1)$$

$$144 G = \left(\frac{T_{B,10.8\mu\text{m}} - T_{B,8.7\mu\text{m}}}{15 K} \right)^{1/2.5} \quad (2)$$

$$145 B = \frac{T_{B,10.8\mu\text{m}} - 261 K}{28 K} \quad (3)$$

146 Here the wavelength in the subscripts denotes the wavelength around which the respec-
 147 tive channel is centered, with the full spectral width depending on the channel (Schmetz
 148 et al., 2002). As a result and as already mentioned, the Dust RGB product features dust
 149 plumes in bright shades of magenta. Quartz-mineral-containing sand surfaces are seen
 150 in light-blue shades. Depending on the cloud type, clouds may feature in Dust RGB im-
 151 ages in brownish shades, black, and/or dark green (Lensky & Rosenfeld, 2008; Banks et
 152 al., 2019).

153 We select data over North Africa, specifically, the region between the longitudes
 154 of 20°W and 52°E and the latitudes of 4°N and 40°N. The region is selected such that
 155 we obtain a quadratic image that is required for the ANN-based algorithm (see Section
 156 2.2.1). The size of each image was reduced to 128 pixels by 128 pixels to increase the com-
 157 putational throughput. This results in each pixel having a dimension of 0.28125° in North-
 158 South-direction and 0.5625° in East-West-direction. Thus, each pixel spans roughly 30
 159 km in the North-South direction and 50-60 km in the East-West direction. A pixel’s arc
 160 length in the East-West direction decreases with increasing distance to the Equator.
 161
 162

163 Both the training process as well as the actual dust plume reconstruction rely on
 164 the operational cloud mask product, referred to as CLM and provided by EUMETSAT
 165 (EUMETSAT, 2009a). The CLM product classifies pixels as either cloudy or clear. Clear
 166 sky pixels are further subdivided according to the surface, i.e., land or water surface. This
 167 classification is performed based on multispectral threshold techniques (Lutz, 1999; Schmetz
 168 et al., 2002). The CLM data used here covers the same region of interest with the same
 169 horizontal resolution as the Dust RGB images.

170 In addition to geostationary satellite data from MSG SEVERI, we also use satel-
 171 lite data from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard
 172 the satellites Aqua and Terra for a comparison of our results. The satellites Terra and
 173 Aqua are orbiting the Earth in a sun-synchronous orbit overpassing the equator in the
 174 morning and afternoon respectively (see e.g., King et al., 2013). Here we use MODIS Level
 175 3 data (Collection 6.1) (MODIS Atmosphere Science Team, 2017b, 2017a). The data was
 176 retrieved using the Deep Blue algorithm, which provides aerosol optical depth (AOD,
 177 τ) and Ångström exponent (α) data over land surfaces (Hsu et al., 2013; Sayer et al.,
 178 2013).

179 *2.1.2 Dust forecasts and reanalysis*

180 In addition to satellite data, our study also uses dust forecast and reanalysis data.
 181 Reanalysis data provides a consistent and global overview of dust AOD τ_{dust} . We use
 182 the dust AOD reanalysis from CAMS (Inness et al., 2019b, 2019a) for training the ANN
 183 (Section 2.2.1). CAMS dust reanalysis data is provided in three-hourly intervals at the
 184 main and intermediate synoptic times, i.e., at 00:00 UTC, 03:00 UTC, and so forth. For
 185 additional analysis, we also use the second Modern-Era Retrospective analysis for Re-
 186 search and Application (MERRA-2) from NASA (Gelaro et al., 2017; Randles et al., 2016,
 187 2017). MERRA-2 provides hourly data starting at 00:30 UTC. For our analysis, the MERRA-
 188 2 dust reanalysis data is linearly interpolated to match the times at which CAMS reanal-
 189 ysis is available.

190 We further use the dust forecast data provided by the World Meteorological Or-
 191 ganization (WMO) Barcelona Dust Regional Center and the partners of the Sand and
 192 Dust Storm Warning Advisory and Assessment System (SDS-WAS) for Northern Africa,
 193 the Middle East and Europe. These dust forecasts cover a geographical area of interest,
 194 which is bound by the longitudes of 25°W and 60°E and the latitudes of 0°N and 65°N
 195 (Terradellas et al., 2022). The WMO Barcelona Dust Regional Center additionally pro-
 196 vides a multi-model median of the available forecast data, which is obtained by regrid-
 197 ding all other models to a shared grid with $0.5^\circ \times 0.5^\circ$ horizontal resolution using bi-
 198 linear interpolation (Basart et al., 2022; Terradellas et al., 2022). Tab. 1 lists the mod-
 199 els, their horizontal resolution, and data availability in 2021 and 2022. Of the models
 200 listed in Tab. 1 only CAMS-IFS, DREAM8-CAMS, NASA-GEOS, and MOCAGE em-
 201 ploy data assimilation. MODIS observations form the backbone of the data assimilation.
 202 Thus, the numerical dust forecasts can be considered independent from SEVIRI obser-
 203 vations. Analogously to the processing of the reanalysis data, the WMO’s forecast data
 204 was selected for our region of interest and remapped bilinearly to the Dust RGB images’
 205 horizontal resolution.

206 Both reanalysis data and numerical dust forecasts were remapped to the Dust RGB
 207 images’ resolution of 128 pixels by 128 pixels with bilinear interpolation using CDO, ver-
 208 sion 2.0.4 (Schulzweida, 2021). The two-dimensional fields at a given time will be referred
 209 to as images.

Table 1. Overview of output from numerical forecast models provided by the WMO Barcelona Dust Regional Center and the partners of the Sand and Dust Storm Warning Advisory and Assessment System (SDS-WAS) for Northern Africa, the Middle East and Europe. Model names are as indicated by WMO Barcelona Dust Regional Center. MULTI-MODEL denotes the median forecast as provided by the WMO Barcelona Dust Regional Center. Note that after 2022-09-29 no further operational forecasts were provided by the BSC-DREAM8b model.

model	domain	horizontal resolution	availability 2021 (days)	availability 2022 (days)	reference
ALADIN	regional	25 km × 25 km	301	210	Termonia et al. (2018); Mokhtari et al. (2012)
BSC-DREAM8b	regional	$\frac{1}{3}^{\circ} \times \frac{1}{3}^{\circ}$	176	120	Nickovic et al. (2001); Pérez et al. (2006); Basart et al. (2012)
CAMS-IFS	global	~ 9 km ^a	324	353	Rény et al. (2019)
DREAM8-CAMS	regional	$\frac{1}{3}^{\circ} \times \frac{1}{3}^{\circ}$	328	360	Pejanovic et al. (2010); Nickovic et al. (2016)
EMA-RegCM4	regional	45 km × 45 km	299	171	Zakey et al. (2006)
ICON-ART	regional	20 km × 20 km	304	340	Rieger et al. (2015)
LOTOS-EUROS	regional	0.5° × 0.25°	316	353	Manders et al. (2017)
MOCAGE	global	1° × 1°	^b	226	El Amraoui et al. (2022)
MONARCH	regional	$\frac{1}{3}^{\circ} \times \frac{1}{3}^{\circ}$	343	345	Pérez et al. (2011); Klose et al. (2021)
NASA-GEOS	global	0.25° × 0.3125°	304	348	Colarco et al. (2010)
NCEP-GEFS	global	1° × 1°	324	343	Lu et al. (2016)
NOA	regional	0.19° × 0.22°	111	235	Flaounas et al. (2017)
SILAM	global	0.5° × 0.5°	222	339	Sofiev et al. (2015)
WRF-NEMO	regional	18 km × 18 km	82	251	Kontos et al. (2021)
ZAMG-WRF-CHEM	regional	0.2° × 0.2°	^b	198	LeGrand et al. (2019)
MULTI-MODEL (median forecast)	-	0.5° × 0.5°	360	365	Basart et al. (2019); Terradellas et al. (2022)

^aCAMS-IFS uses a octahedral reduced Gaussian grid (O1280) with a horizontal distance of 8 – 10 km between grid points (Malardel et al., 2016).

^bForecasts are only available in 2022.

2.2 Dust plume reconstruction

2.2.1 ANN description

Machine learning methods have been increasingly used for automatic image in-painting, i.e., often the repair of damaged or deteriorated photos. In-painting algorithms can be roughly classified into three main types: sequential-based algorithms, convolutional neural net-based algorithms, and generative adversarial networks-based approaches. Convolutional neural networks (CNNs) typically capture the global structure better than sequential-based algorithms (Elharrouss et al., 2020). CNNs have been employed for cloud removal for example by Chen et al. (2020). Another type of ANNs commonly employed in in-painting and subsequently cloud-removal tasks are generative adversarial networks (GANs) (J. Yu et al., 2018; Elharrouss et al., 2020; Jiao et al., 2019; Pajot et al., 2019; Chauhan et al., 2021; Stock et al., 2020; Enomoto et al., 2017; Zi et al., 2022; Li et al., 2020; L. Liu & Hu, 2021). Compared to CNNs, GANs typically require a smaller training data set and are usually capable of reconstructing large-scale or global features. Reconstructions by GANs appear realistic but do not necessarily completely match the ground truth. Similar to the climate data reconstruction by Kadow et al. (2020) we ultimately attempt a classification, for which it may be disadvantageous if the reconstructions do not necessarily match a ground truth. To avoid such disadvantages, we refrained from using algorithms based on GANs and chose an established CNN-based method.

G. Liu et al. (2018) proposed an algorithm based on partial convolutions, which successfully repaired irregular holes in images. Owing to the similarity to convolutional networks for image segmentation, referred to as UNets (Ronneberger et al., 2015), the algorithm possesses a UNet-like architecture (G. Liu et al., 2018). Furthermore, the algorithm was shown to robustly perform regardless of hole size, location, and distance to the image border and outperformed several other algorithms of all three types. Subsequently, the algorithm was adapted to geophysical data by Kadow et al. (2020). This adapted algorithm, climatereconstructionAI (CRAI, Inoue et al., 2022), was successfully used to restore historical temperature anomalies (Kadow et al., 2020). Owing to the robust performance of the original image in-painting algorithm and the successful adaptation to geophysical data, we use the CRAI code as the basis of our work.

The ANN was trained on τ_{dust} data provided by CAMS, introduced in Section 2.1.2. The cloud masks were derived from the temporally corresponding MSG-SEVIRI product. Spatial maps of τ_{dust} from CAMS were temporally matched with the cloud masks from MSG-SEVIRI. We chose to use observed cloud patterns and refrained from using synthetic clouds for training purposes, since the latter may introduce unrealistic patterns during the training process (Enomoto et al., 2017). In addition, both the dust outbreak and the cloud cover are subject to the same atmospheric state, especially the pressure and wind fields. Combining cloud-free satellite images with a set of different cloud masks, thus, would pose the risk of training the ANN on non-physical combinations of cloud and dust patterns. We eliminate such risks by using masks of satellite-observed clouds.

The training was performed on the German Climate Computing Center’s (Deutsches Klimarechenzentrum, DKRZ) cluster Levante. Specifically, we used the cluster’s GPU partition, on which each node consists of two CPUs equipped with AMD 7713 processors and four Nvidia A100 GPUs. The training required ~ 13 hours of wall-time.

For initial tests, the trained neural network was applied to the CAMS reanalysis fields of τ_{dust} from 2022-01-01 to 2022-06-30. Data from this period was excluded in the later validation of the results. Analogously to the training data set, the reanalysis was masked with the MSG-SEVIRI cloud mask product. Fig. 1 shows two-dimensional histograms of the mean CAMS reanalysis on the x-axis and the mean reconstruction on the y-axis. The different panels represent different sizes of the training dataset. The training dataset consists of a total of 16 months, spanning from 2020-09-01 to 2021-12-31 (Fig

1a). For three-hourly time steps as dictated by the reanalysis data with occasionally missing cloud-mask data from SEVIRI, we obtained 3843 pairs of masks and reanalysis "images". This training dataset was augmented by rotating the images by 90° , thus quadrupling the dataset size to a total of 15372 images (Fig 1b). The non-augmented training datasets comprised half a year each, and are shown for summer: 2021-04-01 to 2021-09-30 (1422 images, Fig. 1c) and winter: 2020-10-01 and 2021-03-31 (1449 images, Fig. 1d).

As can be inferred from Fig. 1 and the values of RMSE, MAPE, and r , there is generally good agreement between the mean reconstructed τ_{dust} and the mean τ_{dust} from reanalysis. While the ANN trained for summer marginally outperforms the non-augmented training dataset of 16 months with respect to RMSE, MAPE, and r , we chose the ANN trained on the dataset with 16 months of reanalysis and corresponding cloud mask data (Fig 1a) since it covers more than a full year, which captures some seasonal differences in spatial patterns of τ_{dust} .

To further assess the quality of the reconstruction examples of the unmasked reanalysis (left column) and the corresponding masked reanalysis (center column), and reconstruction (right column) are shown in Fig. 2. The rows represent different examples of reconstructions, showcasing the reconstructions for which we have seen the best performance as well as the two reconstructions with the poorest agreement with the original reanalysis. The first row shows the case of 2022-01-06, 6:00 UTC. For this case, the reconstruction and original reanalysis showed the highest agreement, quantified by both the RMSE and the directed Hausdorff distance. The directed Hausdorff distance is a measure of image (dis)similarity. A directed Hausdorff distance of zero indicates perfect agreement. It will be introduced in more detail in Section 3.3. The reconstruction from 2022-02-03 at 9:00 UTC resulted in an overestimated mean of τ_{dust} . This case is represented by the individual point visible in both top row panels of Fig. 1, which is farthest from the 1:1 line. That difference between reconstruction and reanalysis results in an RMSE of 4.975, the largest between two individual images. Closer inspection in Fig. 2 reveals, that the deviation can be attributed to a limited number of pixels north of the Madeira Archipelago filled with high very high values of τ_{dust} . The reconstruction for 2022-03-16, 03:00 UTC, which has the largest value of the directed Hausdorff distance between the reconstruction and the ground truth, is shown in the third row of Fig. 2. The trained ANN was not able to reconstruct the full spatial pattern of the dust plume, which is the prominent feature of the image's western half. The strong advection of dust over the Iberian Peninsula was not reproduced in the reconstruction. Such infrequent cases of strong dust advection, in which the dust plume is largely obscured by clouds extending to the image boundary over the ocean, can be considered particularly challenging for reconstruction. However, while the reconstruction did not fully reproduce the spatial pattern of τ_{dust} , the reconstruction added information compared to the cloud-masked input. The fourth row shows a case (2022-03-27, 18 UTC) from a period of high mean values of τ_{dust} in the study area. The case from 2022-06-12, 18 UTC, shown in the fifth row, was randomly selected from the month of June 2022.

As demonstrated in Figs. 1 and 2 the trained ANN is capable of successfully reconstructing the cloud-obscured values and patterns of τ_{dust} during the first half of 2022. The reconstruction's purpose is to classify individual pixels as dust-containing or dust-free. Thus, we consider the error stemming from pixels filled with high values of τ_{dust} during the reconstruction, as for the case of 2022-02-03 at 9:00 UTC (see Fig. 2) as negligible.

2.2.2 Gray-scaling of Dust RGB images

To isolate the dust in the satellite observation, the images from MSG-SEVIRI's Dust RGB product were converted to gray-scaled images, where gray corresponds to the pink

312 color assigned to suspended dust in the original product. The gray scaling was based on
 313 perceptual color differences. These perceptual color differences were calculated ac-
 314 cording to definitions by the International Commission on Illumination (Commission In-
 315 ternationale de l'Éclairage, CIE) (Robertson, 1990) in CIELAB color space. To do so
 316 the RGB colors in the images provided by EUMETSAT need to be converted to CIEXYZ
 317 color space and further to CIELAB. The conversion was based on the assumption, that
 318 EUMETSAT uses the sRGB color space, which is the standard for digital online images
 319 (International Electrotechnical Commission, 1999). The conversion to CIEXYZ was per-
 320 formed analogously to the conversion laid out by Fairman et al. (1997); Brill (1998), but
 321 using the conversion matrix values as defined by the sRGB standard (International Elec-
 322 trotechnical Commission, 1999).

323 Each RGB channel has values between 0 and 255. Thus, white would correspond
 324 to (0,0,0) and black to (255,255,255). In the CIEXYZ color space, the luminance is en-
 325 coded in Y and the XZ plane includes all possible chromaticities at a value of Y. In the
 326 CIELAB color space, L^* denotes the lightness, a^* represents the green-red-oriented axis,
 327 and b^* represents the blue-yellow-oriented axis. Negative values of a^* indicate green, whereas,
 328 negative values of b^* indicate blue. The positive values represent red and yellow on the
 329 respective axis (Schanda, 2007). CIELAB forms a Cartesian and nearly uniform color
 330 space, which eases the quantification of perceptual color differences ΔE . ΔE is defined
 331 by (Robertson, 1990)

$$332 \quad \Delta E = [(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2]^{\frac{1}{2}}. \quad (4)$$

333 ΔL^* , Δa^* , and Δb^* denote the differences between the corresponding values of L^* , a^* ,
 334 and b^* of the respective colors.

335 Equation 4 forms the basis of the conversion of Dust RGB images, in which dust
 336 plumes are seen as bright magenta (pink), to gray-scale images. In these gray-scale im-
 337 ages, magenta ($RGB = (255, 0, 255)$) was assigned to white. Colors exceeding a pre-
 338 defined threshold value of the perceptual color difference ΔE compared to magenta were
 339 assigned black. Gray values were assigned based on values of ΔE below the threshold.
 340 We denote the threshold for identifying dust in the image as ΔE_{cut} .

341 We identify the value of the threshold based on earlier studies and own sensitiv-
 342 ity tests. Banks et al. (2019) investigated the effect of different environmental conditions,
 343 such as column water vapor, surface emissivity, skin temperature, and dust layer height
 344 on the color in the RGB Dust product using radiative transfer calculations. This inves-
 345 tigation focused on the months of June and July in 2011, 2012, and 2013. They iden-
 346 tified only a limited number of cases (0.04% of day-time cases and 5.47% of night-time
 347 cases), which resulted in RGB colors with values of the blue channel other than 255. Fig.
 348 3 shows the colors for a fixed value of the blue component of 255 and variable values of
 349 the red (y-axis) and the green (x-axis) components. The corresponding values of ΔE with
 350 respect to magenta with $RGB = (255, 0, 255)$ are shown as isolines. Furthermore, Banks
 351 et al. (2019) provided an overview of the mean colors stemming from the combinations
 352 of aforementioned conditions. For near-pristine cases, the τ_{dust} was assumed to take val-
 353 ues with $\tau_{\text{dust}} \leq 0.2$. For unambiguous cases of dust storms, Banks et al. (2019) set $\tau_{\text{dust}} \geq$
 354 2. Using Eq. 4 the perceptual color difference ΔE between these mean colors reported
 355 by Banks et al. (2019) and magenta with $RGB = (255, 0, 255)$ was calculated. For the
 356 different mean pristine cases, the perceptual color difference takes values with $19.4 \leq$
 357 $\Delta E \leq 129.4$, whereas, for mean cases with a dust load ΔE takes values in the range
 358 of 29.7 and 88.0. However, when additionally taking the skin temperature T_{skin} into ac-
 359 count, the resulting ranges are for cool ($T_{\text{skin}} < 300$ K), pristine mean cases in $19.4 \leq$
 360 $\Delta E \leq 92.6$, for non-cool, i.e., $T_{\text{skin}} > 300$ K, pristine cases $60.2 \leq \Delta E \leq 129.4$. For
 361 cool dust cases ΔE is in the range between 29.7 and 72.3 and respectively in the range
 362 between 31.0 and 88.0 for non-cool dust. As a consequence, the night-time observations,
 363 which are considered to represent the cases of a cool skin temperature are excluded from
 364 the reconstruction. Note, that we use the classification of cases as defined by Banks et

al. (2019). We set the cut-off threshold in our gray-scaling algorithm to $\Delta E_{\text{cut}} = 51.9$, marked with a solid isoline in Fig. 3. With this choice of ΔE_{cut} , pristine cases are not expected to be falsely considered as dust cases, while the true number of dust cases is potentially underestimated. Prior to the process of in-painting (see, Kadow et al., 2020), the gray-scaled images are scaled to values between 0 and 1 as opposed to values between 0 and 255.

Full-resolution Dust RGB images and cloud masks have a spatial resolution in nadir direction of 0.041° or 4.8 km (EUMETSAT, 2009b, 2009a; Schmetz et al., 2002). The images used in this study possess a coarser resolution of 0.28125° in North-South-direction and 0.5625° in East-West-direction. Due to this coarser resolution compared to the full resolution images, it is expected that resampling of the satellite products, especially the Dust RGB product, results in under-counting the number of dust-containing pixels in addition to under-counting due to the choice of ΔE_{cut} (see above). This is expected to mainly concern dust plumes of small spatial scale in one dimension. To gauge the effect of the resampling, the images were resampled from a 128-pixel by 128-pixel grid to a 64-pixel by 64-pixel grid, i.e. each pixel in these coarser resolution images corresponds to 0.5625° in North-South-direction and 1.125° in East-West-direction. Subsequently, we trained another ANN using this coarser resolution. Note, however, that this additionally trained ANN was only used to gauge the impact of the image resolution. We will refer to the images with a size of 128 pixels by 128 pixels as high-resolution images and to the images with a dimension of 64 pixels by 64 pixels as low-resolution images.

We test to what extent the spatial resolution of the satellite data might have an influence on the results. To that end, Figure 4 shows two-dimensional histograms of the fraction of dust-containing pixels in low-resolution images (64 pixels by 64 pixels) and high-resolution images (128 pixels by 128 pixels). Here, observations and the corresponding reconstructions at 9, 12, and 15 UTC were considered. The left panel refers to the direct observations, i.e. the gray-scaled, cloud-obscured Dust RGB images and the right panel refers to the ANN-based reconstructions. The dashed line indicates the best fit, which was obtained by linear regression. Regardless of the resolution, the fraction of dust-containing pixels is generally maintained, as can be inferred from the equation for the best fit and the shape of the histograms. This is also reflected by the Pearson's correlation coefficient of $r = 0.94$ in the case of the direct observations and of $r = 0.93$ in the case of the reconstructions. The reconstruction maintains the general pattern well, as illustrated by the nearly unchanged value of r . Note, that the time required for training on the low-resolution images (64 pixels by 64 pixels) required roughly half the time, compared to the training on the high-resolution images (128 pixels by 128 pixels). Taking the high-resolution images as a reference, the coarser resolution results in a MAPE of the fraction of dust-containing pixels of 46.59% for the observations and 55.04% for the reconstructions. Thus, a finer resolution decreases the under-counting of dusty areas and improves the reconstruction's quality. As a consequence, there are trade-offs between the reconstruction's quality and the reduced risk of under-counting dust-containing pixels on the one hand and the training process' computational demand on the other hand. For the remainder of this study, the higher spatial resolution of 128 pixels by 128 pixels was used to detect more spatial details of dust plumes.

2.2.3 Evaluation methods

The level of agreement between the dust plume extent from our reconstructions and numerical forecasts was evaluated using three different criteria, which have previously been employed to quantify image similarity. The structural similarity index measure (SSIM) quantifies the perceived differences in structural information between two images (Z. Wang et al., 2004). It is a composite measure of means (or luminance), standard deviations (or contrast), and correlation coefficient (or structure) (Z. Wang et al., 2004; Brunet et al., 2012; Palubinskas, 2014). The SSIM takes values between -1 and 1. The higher the agree-

417 ment of two images, the closer the SSIM is to 1. Several studies on image in-painting and
 418 cloud removal applications have used SSIM as an evaluation criterion (e.g., G. Liu et al.,
 419 2018; Qin et al., 2021; Chauhan et al., 2021; Czerkawski et al., 2022; Li et al., 2020; Zi
 420 et al., 2022). We calculate SSIM using the implementation in the software package scikit-
 421 image (van der Walt et al., 2014).

422 Billet et al. (2008) used the directed Hausdorff distance to assess similarities be-
 423 tween two images. As mentioned in Sec. 2.2.1, the directed Hausdorff distance between
 424 two images is the largest distance of a point in the test image to any point in the ref-
 425 erence image. Thus, identical images have a directed Hausdorff distance of 0, and with
 426 increasing differences between the images, the directed Hausdorff distance increases (Huttenlocher
 427 et al., 1993). We calculated the Hausdorff distance of images from our reconstruction
 428 and from numerical forecasts of individual models relative to the image from the median
 429 across all available numerical forecasts, which we chose as a reference. Note, that the di-
 430 rected Hausdorff distance is asymmetric. In other words, the directed Hausdorff distance
 431 from our reconstruction to the median forecast is not necessarily equal to the directed
 432 Hausdorff distance from the median forecast to our reconstruction. In this study the di-
 433 rected Hausdorff distance was calculated using the implementation in SciPy (Virtanen
 434 et al., 2020), which is based on work by Taha and Hanbury (2015).

435 Another commonly used performance evaluation metric in image in-painting and
 436 cloud removal studies (e.g., Sarukkai et al., 2020; Qin et al., 2021; Elharrouss et al., 2020;
 437 Pan, 2020; Zi et al., 2022; G. Liu et al., 2018) is the peak signal-to-noise ratio (PSNR).
 438 The PSNR is defined as (Horé & Ziou, 2013)

$$439 \quad PSNR = 10 \cdot \log_{10} \frac{\max(I_{\text{ref}})^2}{MSE}. \quad (5)$$

440 Here the mean squared error is denoted as MSE. The MSE between an image I and a
 441 reference image I_{ref} , which both consist of $n \cdot m$ pixels is calculated by:

$$442 \quad MSE = \frac{1}{nm} \sum_{i=1}^n \sum_{j=1}^m (I_{ij,ref} - I_{ij})^2 \quad (6)$$

443 For the binary images in our study, $\max(I_{\text{ref}})$ is equal to 1 and Eq. 5 can be simplified
 444 to $PSNR = 10 \cdot \log_{10} MSE^{-1}$. With increasing similarity between two images $MSE \rightarrow$
 445 0, and $PSNR \rightarrow \infty$.

446 3 Results

447 3.1 Case studies

448 We first perform two case studies to test our reconstructions and to gauge their abil-
 449 ity to serve as a tool for evaluating numerical forecasts of dust storms. Here we focus
 450 on observed dust cases that can be considered as hard tests of our proposed method. The
 451 first case concerns a convective dust storm during summer. The numerical models (see
 452 Tab. 1) are not expected to accurately forecast the dust plume, since their horizontal
 453 resolution is too coarse to explicitly simulate convection (cf. Weisman et al., 1997). How-
 454 ever, this may also present challenges for the training data set, since the dust reanaly-
 455 sis depends on available satellite observations as well as an underlying numerical fore-
 456 cast model. The second case study covers a synoptic-scale dust storm in spring. While
 457 the horizontal resolution of the numerical models is not expected to represent a challenge,
 458 the satellite image indicates that a large part of the dust storm is entirely obscured by
 459 clouds, thus providing little guidance on the spatial distribution of the dust plume in the
 460 cloudy sky.

3.1.1 Convective dust storm: 2021-08-22, 09 UTC

The Dust RGB image from 2021-08-22 at 09:00 UTC is characterized by a dust plume extending from Northern Mali to Southern Algeria. Visual inspection of the full-resolution Dust RGB images reveals that dust was originally lofted close to a convective cloud system at around 16:00 UTC on 2021-08-21 near the border between Algeria and Niger. Starting from 23:15 UTC the dust plume decoupled from the motion of the convective system and now followed an independent track. With the chosen threshold of the perceptual color difference of $\Delta E_{\text{cut}} = 51.9$ the gray-scaling approach does not identify the entire dust plume, as can be seen in the top left panel. This serves as an example of potential under-counting of dust pixels (see Section 2.2.2). In Figure 5, the top left panel shows the Dust RGB image in 128 pixels by 128-pixel resolution and highlights by white lines the areas in which dust was detected. The top right panel shows τ as derived from observations by the MODIS instrument aboard Terra. Note that this MODIS Level 3 product does not coincide with 09:00 UTC, but represents the closest overpass of Terra in time. Terra overpasses the Equator at 10:30 local time (cf, King et al., 2013). The panels in the center row show a comparison between the spatial extent of the reconstruction (dark blue shading) and forecasted fields of τ_{dust} from two numerical models (iso-lines). Since the horizontal resolution of the dust forecast model ensemble (see Tab. 1) is too coarse to explicitly simulate deep convection on the model grids (Kain et al., 2008), the forecast models are not expected to accurately predict associated dust plumes (Heinold et al., 2013).

The MODIS/Terra observations of τ also indicate the presence of coarse aerosol at and near the Bodélé Depression in Chad. The DREAM8-CAMS model forecasts a small dust plume near the Bodélé Depression. While the Dust RGB image in 128 pixels by 128-pixel resolution does not indicate the presence of dust plumes at the Bodélé Depression, however, the full-resolution Dust RGB images show the presence of a small dust plume in the Bodélé Depression. As discussed in Section 2.2.2, rescaling Dust RGB images to coarser resolutions leads to undercounting dust events of small spatial extent. Thus, the resulting RGB color values in each pixel may differ too strongly from magenta, i.e. possess large perceptual color differences ΔE . At first, dust emitted by convective systems is completely covered by clouds. Heinold et al. (2013) estimated based on convection-permitting simulations, that up to 90% of afternoon-to-evening dust emissions occur in partly cloudy conditions, and up to 60% of afternoon-to-evening dust emissions occur during strongly cloud-covered conditions, with total cloud cover exceeding 80%. In this case study, dust can first be discerned on the satellite image at 16:00 UTC, making it a prime example of the emission mechanisms discussed by Heinold et al. (2013).

3.1.2 Synoptic-scale dust storm: 2022-03-15, 12 UTC

During mid-March 2022 high loads of Saharan dust were transported to Central Europe via the Iberian Peninsula (cf. A. Seifert et al., 2023). This second case study concerns 12:00 UTC on 2022-03-15. The region of interest's western part is dominated by a cyclone and its associated cloud patterns over the Iberian Peninsula extending southward across Morocco and Algeria. Dust plumes are visible over large areas of Algeria. Furthermore, magenta colors indicate the presence of dust over Chad, Niger, Burkina Faso, Sudan and Egypt. The regional plumes along the border between Burkina Faso and Niger, as well as the ones in Egypt are not displayed in the gray-scaled images, with the exception of a small area in Egypt. As stated in Section 2.2.2 the choice of ΔE_{cut} is such that we use the clearly identifiable dust pixels with intense magenta well aware that this approach leads to a conservative estimate of number of dusty pixels. Specifically, the dust plumes over Egypt are organized as thin streaks, which are less prominently visible after resampling the dust RGB images to a grid of 0.28125° by 0.5625° . It is worth pointing out, that the darker magenta of Southern Niger and Northern Nige-

512 ria is likely caused by clouds, as indicated by visual inspection of the full-resolution im-
 513 ages. Thus, these pixels are correctly identified as dust-free.

514 The reconstructed dust plume stretching from the Iberian Peninsula towards the
 515 Algerian-Malian border is meteorologically plausible. This large dust plume is simulated
 516 by the forecasts of both DREAM8-CAMS and BSC-DREAM8b. However, the dust plume’s
 517 forecasted position over the Mediterranean and the Iberian Peninsula differs from the
 518 reconstruction. In the case of the BSC-DREAM8b forecast, the dust plume extends across
 519 Mali to the Malian-Guinean border region. Visual inspection of the original resolution
 520 images indicates the presence of thin low-level clouds across Mali instead of dust. While
 521 the DREAM8-CAMS dust forecast indicates some dust in Sudan, both models fail to ac-
 522 curately forecast the dust plumes in Sudan and Egypt. The dust plumes in Egypt are
 523 captured by neither the CAMS reanalysis nor the MERRA-2 reanalysis. Both reanal-
 524 ysis products, however, indicate a strong presence of mineral dust with values of $\tau_{\text{dust}} >$
 525 1.1 in Sub-Saharan West Africa. This corresponds to the values observed by MODIS for
 526 coarse aerosol particles. The Dust RGB image, including the full-resolution image, does
 527 not indicate dust this far south. Since both CAMS and MERRA-2 use MODIS satellite
 528 observations to gain information on aerosol properties (Inness et al., 2019b; Rémy et al.,
 529 2019; Gelaro et al., 2017; Randles et al., 2016, 2017), observations from additional satel-
 530 lite sensors may increase the agreement between the reanalysis and the reconstructed
 531 spatial patterns of mineral dust. Furthermore, this case study illustrates, that synoptic-
 532 scale dust storms are still challenges for numerical forecast models, e.g., documented ear-
 533 lier for another case advecting dust over the Iberian Peninsula (Huneus et al., 2016).

534 **3.2 Dust occurrence frequencies**

535 We obtain statistics of dust events by calculating dust occurrence frequencies for
 536 each individual pixel. The maps of the calculated dust occurrence frequencies further
 537 serve as a consistency check, as they can be compared to results from previous studies
 538 including known meteorological drivers of dust emission and transport.

539 **3.2.1 Annual means**

540 Based on the reconstructions dust occurrence frequencies are derived for each in-
 541 dividual pixel at 12:00 UTC.

542 A comparison between reconstructed and directly observed, i.e. non-reconstructed,
 543 dust occurrence frequency for 2021 (left column) and 2022 (right column) is shown in
 544 Fig. 7. We show here the two years separately to illustrate to what extent inter-annual
 545 variability can be inferred for the recent years since the interannual variability was large
 546 for other past years (Wagner et al., 2016). The red shading in the bottom panels indi-
 547 cates that compared to observations without reconstruction, the reconstructed images
 548 indicate an expected higher dust frequency. Notably high differences are seen over the
 549 Atlantic Ocean and along the Atlantic coast. The largest difference inland can be noted
 550 in the Bodélé Depression in Chad, the Tanezrouft Basin in the border region of Alge-
 551 ria and Mali, and the Nubian Desert in Sudan. The differences in the annual dust oc-
 552 currence frequencies for 2021 and 2022 are typically small. A notable exception is the
 553 higher dust occurrence frequency in Iraq during 2022 than in 2021, which was caused
 554 by the heavy dust storms during May and June 2022 (cf. Abdulrahman, 2022; Francis
 555 et al., 2023).

556 For daytime observations, higher values of τ_{dust} result on average in colors closer
 557 to magenta (Banks et al. (2019), specifically Fig. 6 therein) and are therefore better rep-
 558 resented in our reconstruction than weak dust events. Our results show that smaller val-
 559 ues of ΔE_{cut} correspond on average to higher values of τ_{dust} (Fig. 8). Dust occurrence
 560 frequencies for $\Delta E_{\text{cut}} = 20$ corresponds to bright magenta, whereas the $\Delta E_{\text{cut}} = 51.9$

561 include more faded magenta shades and even faded purple shades (compare Fig. 3). Our
 562 studies focuses on $\Delta E_{\text{cut}} = 51.9$, which captures most dust events and reduces the risk
 563 of misclassifications due to ambiguity of processes associated with colors that have a less
 564 pronounced pink component. (see Sec. 2.2.2). For comparison the remaining panels of
 565 Fig. 8 show the dust occurrence frequency obtained from CAMS reanalysis for dust events
 566 with $\tau_{\text{dust}} \geq 0.5$ (center left), $\tau_{\text{dust}} \geq 0.65$ (center right), $\tau_{\text{dust}} \geq 0.9$ (bottom left),
 567 and $\tau_{\text{dust}} \geq 1.1$ (bottom right). Visual inspection and calculation of the PSNR indi-
 568 cate that $\Delta E_{\text{cut}} = 20$ results in the closest match with $\tau_{\text{dust}} \geq 0.9$ and $\Delta E_{\text{cut}} = 51.9$
 569 can be matched with $\tau_{\text{dust}} \geq 0.65$. Over ocean surfaces the perceptual color differ-
 570 ence of $\Delta E_{\text{cut}} = 51.9$ corresponds to values of τ_{dust} of ~ 0.5 , reflecting the influence
 571 of the surface conditions on the dust retrieval. Note, that based on the results by Banks
 572 et al. (2019) the number of dust events can be under-counted with a threshold of the per-
 573 ceptual color difference of $\Delta E_{\text{cut}} = 51.9$ (see Section 2.2.2). Our calculated dust oc-
 574 currence frequency from the reconstructed dust images is therefore still a conservative
 575 estimate, even though dust underneath clouds is now accounted for.

576 The reconstructed patterns of dust occurrence frequency have marked regional max-
 577 ima consistent with previous results for the source activation frequency. Schepanski et
 578 al. (2007, 2012) provided dust source activation frequencies derived from SEVIRI obser-
 579 vations. While these frequencies cannot serve as a validation of the dust occurrence fre-
 580 quency from reconstructed SEVIRI observations, since the latter also include transported
 581 dust, they may serve as a consistency check. From March 2006 to February 2010 strongly
 582 active dust source regions, as identified by Schepanski et al. (2012), were the Tanezrouft
 583 Basin, the Bodélé Depression, and the Nubian Desert. These regions are also display-
 584 ing local maxima in the dust occurrence frequency in 2021 and 2022 shown here (Fig.
 585 7).

586 The local maximum of the dust occurrence frequency from the reconstructed satel-
 587 lite images in the Nubian Desert (close to Sudan’s Red Sea coast) is not represented by
 588 the CAMS reanalysis. The Nubian Desert is a known dust source region as identified ear-
 589 lier in SEVIRI images (Schepanski et al., 2012), and also seen in other aerosol data, e.g.,
 590 the dust emission index derived from data of the Infrared Atmospheric Sounding Inter-
 591 ferometer (Chédin et al., 2020) and the Aerosol Index using observations of the Total
 592 Ozone Mapping Spectrometer (N. J. Middleton & Goudie, 2001). Since the local max-
 593 imum is also present in the dust frequency from non-reconstructed observations, the fea-
 594 ture is not an artifact of the reconstruction. The feature is, however, present in dust oc-
 595 currence frequencies derived from MERRA-2 reanalysis (see Fig. S1). AOD data derived
 596 from MODIS sensors (MODIS Atmosphere Science Team, 2017b, 2017a) for coarse aerosol
 597 particles (Fig. S2) indicates no optically thick, i.e. $\tau \geq 0.7$, dust plumes in the Nubian
 598 Desert during both 2021 and 2022. However, MODIS aerosol data can be (partially) ob-
 599 scured by clouds. Since both CAMS and MERRA-2 use MODIS satellite observations
 600 for aerosol to gain information on their properties (Inness et al., 2019b; Rémy et al., 2019;
 601 Gelaro et al., 2017; Randles et al., 2016, 2017) this difference between CAMS and MERRA-
 602 2 reanalysis is likely attributable to differences between the underlying numerical mod-
 603 els or differences in the assimilation of data. In these models, differences in the emission
 604 of dust are mainly driven by differently simulated winds as well as assumptions on the
 605 soil-surface dependent threshold velocities, which need to be exceeded for dust emission
 606 (e.g., Inness et al., 2019b; Randles et al., 2017).

607 **3.2.2 Seasonal cycle**

608 The spatial patterns of seasonal dust occurrence from the reconstruction are re-
 609 markably consistent with the dust source activation frequency from March 2006 to Febru-
 610 ary 2007 as reported by Schepanski et al. (2007). The spatial pattern for 2021 and 2022
 611 also shows consistency with the dust occurrence frequency derived from a combination
 612 of MODIS AOD data with Aerosol Index data from the Ozone Monitoring Instrument

(OMI) for 2005–2019 as reported by Gavrouzou et al. (2021). This similarity allows us to infer dominant meteorological processes driving the dust occurrence in the following.

Dust emission and dust transport in North Africa are known to be subject to diurnal, seasonal, annual, and inter-annual differences (e.g., Engelstaedter et al., 2006). The seasonal mean dust occurrence frequency averaged for 2021–2022 is shown in Fig. 9. For comparison, occurrence frequencies for coarse aerosol particles with $\tau_{\text{dust}} \geq 0.65$ from MODIS Level 3 data are used. The threshold of $\tau_{\text{dust}} \geq 0.65$ was chosen, based on the comparison of reconstruction-derived dust occurrence frequencies with CAMS reanalysis-derived dust occurrence frequencies (see Fig. 8), which yields the best match with respect to the PSNR between the resulting spatial patterns. The right column of Fig. 9 specifically shows the mean of the Level 3 product from MODIS on board Terra and Aqua. Following the work by Basart et al. (2009), we counted dust events for which the threshold of τ was reached and for which simultaneously the Ångström exponent was $\alpha < 0.75$. Note, that Basart et al. (2009) used Ångström exponent data between the wavelength pair of 440 nm and 870 nm, whereas, the values from MODIS Ångström exponent data are for the wavelength pairs of 412 nm and 470 nm (over bright scenes, such as deserts) or else between 470 nm and 650 nm (Hsu et al., 2013).

We identify distinct seasonal differences in the spatial patterns of dust obscured by clouds, based on the differences between the dust occurrence frequency derived directly from original SEVIRI observations and those derived from the ANN-based reconstruction. In winter, dust plumes primarily close to the Bodélé Depression are obscured by clouds. During spring, the effects of obscuring clouds in the Bodélé Depression can still be clearly recognized, but the effect is now more evenly spread over the entire region of interest. Summertime cloud obscuring mainly occurs in Mali, Algeria, and to a lesser extent in Niger, as well as in the Nubian desert. As dust activity during autumn is generally lower compared to the other seasons, the number of dust events obscured by clouds is also smaller.

The spatial patterns of the cloud occurrence frequency, f_{cloud} , as derived from MODIS observations (see Fig. S5) during winter and spring display a remarkable similarity between each other. With the exception of the Bodélé Depression, where during winter $f_{\text{cloud}} \sim 50\%$, f_{cloud} was 20–40% in the in-land locations of the study region north of $\sim 13^\circ\text{N}$. For better visual guidance, this latitude approximately falls onto the Nigerien-Nigerian border. During spring, dust plumes extend further southwards than during summer, which is due to seasonally different dust transport directions associated with seasonal variations in the atmospheric dynamics over Northern Africa (Schepanski et al., 2009). During summer, for instance, high cloud occurrence is expected further inland due to deep convection associated with the West African Monsoon (see Fig. S5).

The identified spatial patterns of dust occurrence agree with known dust emission and transport processes. For instance, the dust occurrence in spring along the Mediterranean coast is associated with moving cyclones, which primarily occur in spring along the North African Mediterranean coast and transport dust east- and north-wards (Israelevich et al., 2002). The absolute differences between dust occurrence derived from direct SEVIRI observations and the reconstructions take values of 2–3 pp along North Africa’s Mediterranean coast (see Fig. 7) indicative of an underestimation of dust occurrence in satellite images due to clouds during cyclones, also known as Sharav cyclones (Alpert & Ziv, 1989; Israelevich et al., 2002). In spring, up to 90% of North African dust emissions north of 25°N and west of 10°E are associated with depressions, and up to 25% of dust emissions along the Mediterranean Sea’s coast are linked to mobile cyclones (Fiedler et al., 2014).

Between November and March, dust is transported towards regions south of the Sahel by north-easterly near-surface trade winds, referred to as Harmattan (Warner, 2004; Oluleye & Jimoh, 2018). The dust occurrence south of the Sahel in spring is attributable

665 to the Harmattan. The summertime dust occurrence in West Africa, mostly in Algeria,
 666 Mali, and Niger, is also commonly linked to depressions, also known as the West African
 667 heat low (Fiedler et al., 2014). More specifically, summertime dust emission can be linked
 668 to strong near-surface winds generated by low-level jets and convective cold pools (Fiedler
 669 et al., 2013; Heinold et al., 2013). Convective cold pools are generated by downdrafts
 670 from deep moist convection and hence are associated with the presence of clouds (Roberts
 671 & Knippertz, 2014; Trzeciak et al., 2017; Caton Harrison et al., 2019; Allen & Washing-
 672 ton, 2014). Especially, the timing of the onset of dust emission is missed by satellite ob-
 673 servations due to the clouds during such conditions. The aspects pertaining to the di-
 674 urnal cycle will be discussed in Section 3.2.3.

675 The severe Middle Eastern dust storms in May and June 2022 (Abdulrahman, 2022;
 676 Francis et al., 2023) resulted in high values of dust occurrence frequency, which can be
 677 seen in Iraq, Iran and Saudi Arabia, during both spring and summer as seen by com-
 678 paring the seasonal dust occurrence frequency in 2021 against 2022 (Fig. S3).

679 During winter and spring a comparatively large number of events with $AOD_{\text{coarse}} \geq 0.65$
 680 was detected in sub-Saharan North Africa from MODIS, which is not as strongly pro-
 681 nounced in the reconstruction of SEVIRI images. A small number of regional dust cases
 682 (with $f_{\text{dust}} < 5\%$) is here indeed seen in the reconstructed SEVIRI images, however,
 683 in general, no frequent dust events are detected in sub-Saharan North Africa by SEVIRI.
 684 Earlier investigations of the dust source activation frequencies derived from MODIS AOD
 685 and OMI Aerosol Index display here a different spatial pattern compared to SEVIRI-
 686 derived dust source regions. MODIS-derived dust source regions are located further south
 687 than most of the SEVIRI- and OMI-derived dust source regions. The SEVIRI-derived
 688 dust source regions stretch across North Africa from Western Sahara and Morocco in the
 689 west until Sudan in the east. Observations from all three sensors indicate a dust source
 690 region in Niger and Chad, which includes the Bodélé Depression (Schepanski et al., 2012).
 691 Since winter and spring are outside the North African biomass burning season (Barbosa
 692 et al., 1999) and by taking only coarse aerosol ($\alpha < 0.75$) into account, the risk of mis-
 693 classifying other types of aerosol particles as dust is reduced but not entirely eliminated.
 694 Dust occurrence frequencies derived by SEVIRI and occurrence frequencies based on AOD
 695 and Ångström exponent thresholds derived from MODIS Level 3 data are not directly
 696 comparable. One reason is that other aerosol species than mineral dust are also included
 697 in the AOD of MODIS, e.g., anthropogenic and biogenic aerosols. Another reason lies
 698 in the orbits of Terra and Aqua. Each MODIS overpass over a specific location corre-
 699 sponds to a certain time. The MODIS Level 3 products aggregate the observations into
 700 a single dataset. These differences limit the comparability between observations of aerosols
 701 from MODIS and SEVIRI. Regardless of the systematic differences, the two results agree
 702 on identifying seasonal patterns of dust occurrence frequency. For instance, both SEVIRI
 703 and MODIS observations identify the Bodélé Depression as an important dust source
 704 during winter and spring, as well as, highlighting widespread dust occurrence in West
 705 Africa during summer.

706 As already evident from Fig. 8, with $\Delta E_{\text{cut}} = 51.9$ a higher number of optically
 707 thinner ($0.5 \leq \tau_{\text{dust}} < 0.65$) dust plumes are detected over ocean than over land. This
 708 difference in the detection sensitivity between land and ocean is especially prominent dur-
 709 ing the spring months (MAM) and during the winter months of 2021 (cf. Fig. 9). Fig.
 710 8 also indicates that the dust occurrence frequency derived with $\Delta E_{\text{cut}} = 20.0$, which
 711 corresponds to bright magenta colors, is less sensitive to transitions between land and
 712 ocean backgrounds. Surface characteristics, specifically differences in emissivity and skin
 713 temperature, affect the color in the Dust RGB images resulting in rather purple shades
 714 in the presence of dust plumes. By considering only bright magenta colors, we select cases
 715 in which the effect of different surface conditions is less prominent, hence the transition
 716 between land and ocean background is smoother.

To gauge the influence of the value of ΔE_{cut} , we show the seasonal dust occurrence frequency during 2021 and 2022 derived from images with $\Delta E_{\text{cut}} = 20.0$ in Fig. 10. The interannual differences in the dust occurrence frequency between 2021 and 2022 are shown in Fig. S4. As mentioned earlier, the threshold of $\Delta E_{\text{cut}} = 20.0$ results in only pixels colored brightly magenta being classified as dust-containing. Thus, the dust occurrence frequency is lower compared to $\Delta E_{\text{cut}} = 51.9$ which includes also more purple colors for dust detection. However, not only the magnitude but also the spatial patterns change when setting $\Delta E_{\text{cut}} = 20.0$, specifically during winter and spring, whereas, the spatial patterns over land during summer and autumn remain largely similar, with little overall activity in autumn. Dust occurrence in both winter and spring is connected to transport by mobile cyclones along the Mediterranean coast (e.g., Engelstaedter et al., 2006; Bou Karam et al., 2010) and southward transport towards sub-Saharan Africa and the Gulf of Guinea (e.g., Schwanghart & Schütt, 2008; Schepanski et al., 2009; Oluleye & Jimoh, 2018). In both cases, dust plumes become more frequently mixed with moister air, resulting in purple-colored pixels in the Dust RGB images, which are not detected assuming $\Delta E_{\text{cut}} = 20$. Summertime dust events in West Africa can be associated with convective systems (cf., Nickling & Gillies, 1993; Schwanghart & Schütt, 2008; Heinold et al., 2013; Bou Karam et al., 2014; Roberts & Knippertz, 2014; Allen & Washington, 2014), which feature in bright magenta in the Dust RGB images and are, consequently, detected with both values of ΔE_{cut} . Transported dust even during summertime can feature in purple and faded magenta shades (see Sec. 3.1) and, thus, account for pattern differences.

Dust emitted from the Bodélé Depression during winter and spring was only sparsely detected in 2021 and not at all in 2022 when we used $\Delta E = 20$ as a threshold since here the dust plumes result in less brightly magenta colors in the Dust RGB images. The dust occurring during winter over the Atlantic Ocean to the northwest of the Madeira Archipelago is an artifact produced by the ANN since here little dust occurs in combination with clouds and hence the training data might be too small. During spring 2021 the maximum dust occurrence is along the Malian-Burkinabé border with no dust detected in Northern Mali. This local maximum can be attributed to multiple dust events in early May, which resulted in bright magenta shades in the Dust RGB product.

3.2.3 Diurnal cycle

We assess the diurnal cycle in the dust occurrence frequency by extending our analysis from 12 UTC shown so far to 9 and 15 UTC. These additional reconstructions were performed using gray-scaled SEVIRI images with $\Delta E_{\text{cut}} = 51.9$ for 9 and 15 UTC. Fig. 11 shows the absolute differences in dust occurrence frequency at 9 (left column) and 15 UTC (center column) respectively with respect to 12 UTC.

The annual dust occurrence frequencies indicate high values of the dust occurrence frequency in the Bodélé Depression at 9 UTC. The breakdown into seasons shows clearly, that at 9 UTC dust events in the Bodélé Depression mainly occur during winter and spring, consistent with the mid-morning breakdown of nocturnal low-level jets generating dust-emitting winds (Fiedler et al., 2013). In the left-hand column of Fig. 11 the larger occurrence at 9 UTC is seen by the red shades at the location of the Bodélé Depression, marked by a black star in the right-hand column. This finding is further consistent with other data shown by Washington et al. (2009), according to which dust in 2006 and 2007 in the Bodélé Depression was mainly emitted between 6 and 9 UTC. As can be seen in Fig. 11 dust is then mainly transported towards the southwest. This gives rise to the dipole structure visible in the absolute differences between dust occurrence frequencies at 9 and 12 UTC and 15 and 12 UTC respectively in Chad and along the border of Chad and Niger. This transport pattern is consistent with dust transport from the Bodélé Depression in January, February, and March 1979 to 1997 (Washington et al., 2006).

768 The absolute differences in dust occurrence frequency over the Arabian peninsula
 769 at 15 UTC reach up to 15 pp compared to 12 UTC. These are likely caused by dust lift-
 770 ing due to convection. Mesoscale convective systems over the southern Arabian Penin-
 771 sula typically occur during winter and spring with a local maximum at 14–15 UTC (Nelli
 772 et al., 2021). Note, that the highest number of mesoscale convective systems was reported
 773 between 22 and 23 UTC, a time not covered by this study. The combination of solar heat-
 774 ing, local circulations, and cyclonic activity during winter and spring drive convection
 775 on the Arabian Peninsula (Warner, 2004). Numerical studies point to dry convection and
 776 to a lesser extent moist convection as an important driver of dust emission on the Ara-
 777 bian Peninsula (Bukowski & van den Heever, 2020). Field observations in Morocco fur-
 778 ther indicate the importance of convection for dust emission (Ansmann et al., 2009). At
 779 15 UTC, which corresponds to roughly 18 LT, beginning surface cooling after sunset in
 780 the Eastern parts of the studied region may further begin to distort the values of dust
 781 occurrence frequency. As discussed in Sec. 2.2.2, for skin temperatures with $T_{\text{skin}} < 300$ K
 782 the dust plumes are no longer clearly distinguishable from other environmental impacts
 783 on the Dust RGB product. Such conditions can be reached after sunset.

784 As stated above among the processes contributing to summer-time dust emission
 785 in the Sahara, specifically the region characterized by a local maximum in dust occur-
 786 rence frequency situated in northern Mali, southern Algeria, and north west Niger, are
 787 low-level jets and cold pool outflows. Field observations during June 2011 in Bordj-Badji
 788 Mokhtar (southern Algeria, 21.33°N, 0.95°E) indicate a maximum in surface-level wind
 789 speeds (at 10 m a.g.l.) with the breakdown of low-level jets, i.e., typically between 9 and
 790 10 UTC which corresponds to 10 – 11 LT (Allen & Washington, 2014). Numerical sim-
 791 ulations of dust emission between 2006-07-26 and 2006-09-02 by Heinold et al. (2013)
 792 indicate an earlier maximum in the mean hourly dust emission over West Africa at 8 UTC.
 793 Considering the continued dust emission after 8 UTC and the time needed for the freshly
 794 emitted dust to be upward mixed and transported as seen in the satellite images, the higher
 795 values of dust occurrence frequency at 12 UTC over West Africa during summer in our
 796 results are broadly consistent with Heinold et al. (2013) and Allen and Washington (2014).

797 3.3 Evaluation of forecast data

798 The trained neural network was applied to all available gray-scaled SEVIRI images
 799 from 2021 and 2022 at 12:00 UTC. Here, we use the resulting images to evaluate the out-
 800 put of dust forecast provided by the World Meteorological Organization (WMO) Barcelona
 801 Dust Regional Center (see Section 2.1.2). Since qualitatively reconstructed images of ar-
 802 eas with dust and quantitative forecasts of the dust aerosol optical depth are not directly
 803 comparable, we first convert both the reconstructed gray-scale satellite images and the
 804 forecasted fields of τ_{dust} to binary images in which 1 represents a "dusty" pixel and 0
 805 a dust-free pixel. In the case of the dust forecasts, a pixel is classified as dusty, if the AOD
 806 exceeds a pre-defined threshold, i.e., $\tau \geq \tau_{\text{threshold}}$. For this purpose, we define and test
 807 six different thresholds: $\tau_{\text{threshold}} = [0.3, 0.5, 0.7, 0.9, 1.1, 1.3]$.

808 Fig. 12 compares the dust forecast ensemble with respect to the median forecast,
 809 provided by the WMO Barcelona Dust Regional Center, and the forecast ensemble with
 810 respect to the reconstruction for both 2021 and 2022. The evaluation metrics SSIM, di-
 811 rected Hausdorff distance, and PSNR (Section 2.2.3) are displayed as violin plots (Hintze
 812 & Nelson, 1998) to evaluate the regional performance. As the median forecast is com-
 813 posed of the other model forecasts within the ensemble, we expect a larger number of
 814 cases with $SSIM \approx 1$ when we compare the individual forecast models against the me-
 815 dian of all forecasts than for the reconstruction compared to the median of all forecasts.
 816 For small lower bounds of AOD ($\tau_{\text{min}} \geq [0.3, 0.5]$) the distribution of SSIM val-
 817 ues for forecasts compared to median forecasts strongly differ from the reconstructions
 818 compared to the median of forecasts. For intermediate AOD bounds ($\tau_{\text{dust}} = 0.7$) the
 819 difference in the value distributions is reduced, although for the reason outlined above

820 the forecasts as a whole yield values of SSIM closer to 1. For larger values of AOD bounds
821 $SSIM \rightarrow 1$, however, the forecasts converge faster to 1 than the reconstructions.

822 Using the directed Hausdorff distance as an evaluation criterion the reconstruction
823 performs with respect to the dust forecast ensemble on average as well as the forecast
824 ensemble compared to the median forecast for values of $\tau_{\text{threshold}} \geq 0.7$. In the case of
825 PSNR, the reconstruction with respect to the forecast ensemble performs best for $AOD_{\text{threshold}} =$
826 0.7 compared to all model forecasts with respect to the median forecast, although the
827 performance differences are not large. For $\tau_{\text{threshold}} \geq 0.9$ the median forecast outper-
828 forms the reconstruction with respect to the PSNR.

829 We use the reconstruction of dust plumes to assess the level of similarity of dust-
830 plume extents simulated by individual numerical forecasts over North Africa next. Fig-
831 ure 13 allows us to compare the reconstruction’s performance against the output from
832 individual forecast models. In 2021 (top row) the models BSC-DREAM8b, DREAM8-
833 CAMS, and WRF-NEMO agree best with the reconstruction as indicated by the respec-
834 tive median values of all three metrics. In 2022 (bottom row) the highest agreement in
835 terms of PSNR and directed Hausdorff distance is seen for DREAM8-CAMS, MOCAGE,
836 and WRF-NEMO, and in terms of SSIM for DREAM8-CAMS, MOCAGE, NCEP-GEFS
837 and ICON-ART. Only evaluating the spatial patterns, LOTOS-EUROS and MONARCH
838 performed poorest in both 2021 and 2022. While outperforming LOTOS-EUROS and
839 MONARCH with respect to all three evaluation metrics, NCEP-GEFS performed third
840 poorest in 2021. In 2022 NOAA, which in 2021 narrowly outperformed NCEP-GEFS, had
841 the third poorest performance. It should be noted, that among the best-performing mod-
842 els, both DREAM8-CAMS and MOCAGE use data assimilation, while none of the mod-
843 els with comparatively poor performance used data assimilation techniques. It should
844 be stressed, that our evaluation has a focus on the spatial pattern of dust plumes, which
845 was not done in the past. Typically, dust model forecasts are evaluated by their ability
846 to correctly forecast τ at monitoring stations, most of which stem from sunphotometers
847 that can only provide data during daytime in cloud-free conditions (cf. Huneeus et al.,
848 2011; Terradellas et al., 2022). Hence, our study has demonstrated a new capability to
849 evaluate simulated dust transport with a first consideration of dust plume shapes, based
850 on computationally fast reconstructions of dust plumes in satellite images.

851 4 Discussion and Outlook

852 In this study, we restored spatial patterns of dust plumes from partially cloud-obscured
853 satellite observations for the first time. Since both dust-aerosol emission and transport
854 and cloud structures are governed by atmospheric conditions, we combined dust AOD
855 data from CAMS reanalysis with coinciding SEVIRI-derived cloud-masks for the train-
856 ing of the ANN. The trained network was applied to cloud-masked, gray-scaled satel-
857 lite images, derived from MSG-SEVIRI’s Dust RGB product. The reconstruction of dust
858 plumes performs just as well or better than individual forecasts relative to the median
859 across all forecasts.

860 Our dust occurrence frequency from the reconstructed dust plumes is consistent
861 with spatial patterns of the dust source activation frequency reported in earlier studies
862 and with the understanding of atmospheric processes driving dust emission and trans-
863 port. So far parametrizations in numerical models provided a way of gauging the extent
864 of below-cloud dust events, i.e. of ”seeing” beneath the clouds. By applying machine-
865 learning-based in-painting methods to geostationary satellite images, we demonstrated
866 another possibility of estimating the full extent of dust events. Compared to numerical
867 modeling, once the ANN is trained, our approach is computationally much cheaper than
868 numerical modeling. Provided a SEVIRI Dust RGB image and the corresponding cloud
869 mask are available, gray-scaling, data conversions, and subsequent in-painting for a sin-
870 gle image required 30 seconds on a single core (AMD 7763 CPU, provided by DKRZ).

871 Note, that this is an upper bound of required resources since the computational set-up
872 was not streamlined for (near) real-time image processing.

873 Comparing the reconstructed and the directly observed dust occurrence frequen-
874 cies for both 2021 and 2022 (see Fig. 7) indicates, that previous studies of the dust oc-
875 currence frequency and by extension the dust source activation frequency derived from
876 SEVIRI and other satellite observations underestimate the dust occurrence and dust source
877 activation due to the presence of clouds (e.g., Schepanski et al., 2012; Heinold et al., 2013;
878 Chédin et al., 2020). Our results suggest that at least 0.78% of observations in the spa-
879 tial mean over the entire region of interest miss dust events due to cloud coverage. Re-
880 gionally and seasonally dust missed due to clouds can be up to 15% of observations. In
881 extreme cases, all dust events occurring in an individual pixel are obscured by clouds.
882 In 7.3% of pixels, all dust events as obtained by our proposed reconstruction method would
883 be missed using conventional satellite observations. In 29.5% and 17.7% of pixels at least
884 a tenth and a half of all dust events in the reconstruction, respectively, coincide with cloud
885 coverage. When considering only the events with $\tau_{\text{dust}} \geq 0.65$ (see 8) in the CAMS re-
886 analysis as dust events, then for 9.6% of pixels of all dust events coincide with a cloud
887 as observed by SEVIRI. A tenth and a half of dust events from CAMS reanalysis coin-
888 cide with cloud coverage in 84.3% and 55.4% respectively of the pixels. Owing to our
889 choice of identifying dust events by using gray-scaling based on perceptual color dif-
890 ferences and due to the resolution of the input images, our number of dust events is still
891 likely to be a conservative estimate, as indicated by the two case studies. In close prox-
892 imity to clouds, the under-counting of dust-containing pixels can still be rectified by the
893 ANN-based reconstruction method as illustrated in the first case study.

894 Since a similar Dust RGB composite is provided operationally for observations by
895 the Advanced Baseline Imager (ABI) instrument onboard the Geostationary Operational
896 Environmental Satellite (GOES) and the Advanced Himawari Imagers (AHI) onboard
897 the geostationary Himawari satellite, our approach could be transferred to other regions
898 of interest (cf. Fuell et al., 2016; Bessho et al., 2016). While this study was focused on
899 data from geostationary satellites the in-painting approach can also be adapted to ob-
900 servations and products from polar-orbiting satellites, such as AOD products derived from
901 MODIS. Provided suitable training data from reanalysis is available the approach can
902 further be applied to observations of different aerosol species and plumes of trace gases
903 close to the respective source.

904 The here proposed method to restore dust plume extents on SEVIRI RGB Dust
905 images by machine-learning-based image in-painting methods can be applied to a larger
906 area and to images at a higher temporal resolution of up to 15 minutes in the case of SE-
907 VIRI. Such a spatial extension can facilitate additional investigations of dust transport
908 to Europe and/or across the Atlantic Ocean. Using a higher temporal resolution may
909 aid in studying dust transport mechanisms within North Africa in more detail and help
910 to overcome observational gaps stemming from sparse ground-based observations.

911 There are a number of aspects in our current approach that can be further refined
912 for future applications. To obtain a consistent spatio-temporal picture of suspended dust,
913 the values of ΔE_{cut} can be adjusted to the different environmental conditions, such as
914 surface type (surface emissivity), skin temperature, and a climatology of column water
915 vapor content (see Section 2.2.2 and Banks et al. (2019)), e.g., via generating look-up
916 tables to account for these aspects. Adapting ΔE_{cut} to different environmental condi-
917 tions would also be the next step to develop a link of the Dust RGB product or derived
918 products, such as our reconstructed images, to τ_{dust} . Currently, there are already retrievals
919 of dust AOD from SEVIRI observations based on look-up tables of observed shortwave
920 reflectance (Brindley & Ignatov, 2006) for retrievals over ocean surfaces and based on
921 longwave brightness temperatures in conjunction with European Centre for Medium-Range
922 Weather Forecasts’ operational analysis for retrievals over land surfaces (Brindley & Rus-
923 sell, 2009), which could be exploited. Other retrieval algorithms involve optimal estima-

924 tion (cf. Rodgers, 2000) based on observed brightness temperatures at both visible and
 925 infrared channels (Carboni et al., 2007; Thomas et al., 2009). Following successfully es-
 926 tablished links between AOD and the color in the RGB Dust product, our method can
 927 restore the cloud-obscured fractions of AOD and subsequently contribute to assimilating
 928 further satellite observations into numerical models to better constrain the forecasts
 929 of dust. Accurate forecasts of dust plumes are important for different applications, e.g.,
 930 in the health and energy sector.

931 So far, each image has been reconstructed individually. With the help of recurrent
 932 neural networks (Che et al., 2018) the temporal evolution of dust storms can be taken
 933 into account explicitly by the network, thus, potentially further improving the reconstruc-
 934 tions. While ground-based observations of dust in Northern Africa are sparse, incorpo-
 935 rating these observations into the reconstructions provides another avenue for potential
 936 improvements in dust storm reconstruction for a better understanding of their evolution
 937 and accurate warnings of their impacts.

938 5 Conclusion

939 We present to our knowledge the first fast reconstruction of the spatial extent of
 940 partially cloud-obscured dust plumes from satellite observations. We achieve this by em-
 941 ploying machine-learning-based image inpainting techniques. Once the artificial neural
 942 network is trained, the reconstruction of dust plume extents is computationally inexpen-
 943 sive.

944 Spatially averaged over North Africa the differences in annual dust occurrence be-
 945 tween reconstructions and classical satellite observations are small, not at last because
 946 dust is not present all the time across the entire of North Africa. However, the number
 947 of dust events obscured by clouds increases, when considering seasonal and regional sub-
 948 sets. As a conservative estimate, we find that up to 15% of satellite observations in West
 949 Africa and up to 10% of satellite observations in the Nubian Desert during 2021–2022
 950 miss dust events. Based on the reconstructed plumes, in 7.3% of pixels, all dust events
 951 coincide with clouds and would, thus, not be directly identifiable from classical satellite
 952 observations. This roughly corresponds to a geographical area of $\sim 2 \cdot 10^6$ km². Our
 953 comparison with reanalysis indicates a somewhat higher fraction of 9.6% of pixels in which
 954 all dust events coincide with cloud cover.

955 The reconstructed dust plumes provide new means to validate and constrain spa-
 956 tial patterns of dust plumes in simulations from numerical forecast models and Earth
 957 system models. They further provide means for more detailed studies of dust emission
 958 and transport mechanisms using satellite observations free of gaps caused by cloud cover
 959 for the first time. The method can be applied to the corresponding dust products ob-
 960 tained from sensors on other geostationary satellites to compile a global dataset. It can
 961 also be adapted to different types of aerosols and trace gases observed from geostation-
 962 ary and low-earth orbit satellites to broaden the possibilities for model validation of at-
 963 mospheric composition in models, e.g., as simulated by Earth system models in the Cou-
 964 pled Model Intercomparison Project (CMIP).

965 Open Research Section

966 The code for the ClimateReconstructionAI can be obtained from Zenodo (Inoue et
 967 al., 2022). The gray-scaling algorithm can be obtained from <https://github.com/tobihose/Masterarbeit>.
 968 Dust forecast datasets were provided by the WMO Barcelona Dust Regional Center and
 969 the partners of the Sand and Dust Storm Warning Advisory and Assessment System (SDS-
 970 WAS) for Northern Africa, the Middle East and Europe and can be obtained from <https://dust.aemet.es>.
 971 CAMS reanalysis data were provided by the Copernicus Atmospheric Monitoring Ser-
 972 vice (Inness et al., 2019a) and can be obtained from <https://ads.atmosphere.copernicus.eu>.

SEVIRI false color RGB images (collection ID: EO:EUM:DAT:MSG:DUST, EUMETSAT (2009b)) and MSG cloud masks (collection ID: EO:EUM:DAT:MSG:CLM, EUMETSAT (2009a)) were provided by EUMETSAT and can be obtained from the EUMETSAT Data Store under <https://data.eumetsat.int>. MERRA-2 reanalysis data (Global Modeling And Assimilation Office & Pawson, 2015) was provided by the National Aeronautics and Space Administration's (NASA) Goddard Earth Science Data Information and Services Center (GES DISC) and can be obtained from <https://disc.gsfc.nasa.gov/datasets?project=MERRA-2>. MODIS level 3 data (MODIS Atmosphere Science Team, 2017b, 2017a) was provided by NASA and can be obtained from <https://ladsweb.modaps.eosdis.nasa.gov>. Access to all datasets requires prior registration. In-painted images generated in the course of this study, as well as, trained ANNs will be made available on Zenodo with the publication of the study.

Acknowledgments

We acknowledge internal funding by the GEOMAR Helmholtz Centre for Ocean Research Kiel and University of Cologne for this work. We are grateful to Naoto Inoue, Christopher Kadow, and Stephan Seitz for making the climatereconstructionAI code publically available and to Johannes Meuer and Étienne Plésiat for maintaining the code. Tobias Höschen is acknowledged for developing the grey-scaling algorithm as part of his master's thesis work, which was co-supervised by S. Fiedler. Dust forecast data was provided by the WMO Barcelona Dust Regional Center and the partners of the Sand and Dust Storm Warning Advisory and Assessment System (SDS-WAS) for Northern Africa, the Middle East and Europe. This work used resources of the Deutsches Klimarechenzentrum (DKRZ) granted by its Scientific Steering Committee (WLA) under project ID 1198.

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1599 Fig. 1. Two-dimensional histograms of the mean non-masked τ_{dust} from CAMS re-
 1600 analysis and the mean reconstructed τ_{dust} . The shading represents the density of the data
 1601 points in the respective size bin with white indicating no available data. For each panel,
 1602 the root mean squared error (RMSE) and the mean absolute percent error (MAPE) of
 1603 the reconstruction with respect to the reanalysis are given. Furthermore, the Pearson
 1604 correlation coefficient r between reconstructed and original, i.e., non-masked, reanaly-
 1605 sis is shown.

1606 Fig. 2. Comparison of CAMS reanalysis used as ground truth (left column), cloud-
 1607 masked CAMS reanalysis, used as input (center column), and reconstruction (right col-
 1608 umn) for 5 different cases, represented by the rows. Note, that rows 2 and 3 represent
 1609 the reconstructions resulting in the largest deviations from the ground truth with respect
 1610 to RMSE (case 2022-02-03, 09:00 UTC) and directed Hausdorff distance (case 2022-03-
 1611 16, 03:00 UTC).

1612 Fig. 3. RGB colors as a function of value of the red component (along y-axis) and
 1613 the green component (along x-axis) for a fixed value of the blue component of 255. Iso-
 1614 lines indicate perceptual color differences ΔE calculated using Eq. 4. For most parts
 1615 of our study, we set $\Delta E_{\text{cut}} = 51.9$, indicated by the solid line.

1616 Fig. 4. Two-dimensional histograms showing fraction of dust containing pixels in
 1617 the gray-scaled, cloud-obscured Dust RGB images in coarser and finer resolution (left)
 1618 and the ANN-based reconstruction (right). Shading is as in Fig. 1. The dashed line in-
 1619 dicates the best fit, obtained by using linear regression.

1620 Fig. 5. Comparison of SEVIRI and MODIS observations with results from numer-
 1621 ical dust forecasts, ANN-based reconstructions and reanalysis data for 2021-08-22, 09
 1622 UTC. Top right panel show Dust RGB image in 128 pixel by 128 pixel resolution and
 1623 dust plumes detected by applying gray-scaling are indicated by white contours. The top
 1624 left panel shows τ from MODIS/Terra observations for coarse particles ($\alpha > 0.75$) with
 1625 isolines indicating the different values. The middle panels show the reconstructed dust

1626 plumes in dark blue and the isolines show the forecasted values of τ_{dust} . The forecast shown
 1627 in the left panel was obtained from the DREAM8-CAMS model and the forecast in the
 1628 right panel from the NASA-GEOS model. The bottom panels show SEVIRI Dust RGB
 1629 images as in the top right panel. White, hatched contours indicate reconstructed dust
 1630 plumes, whereas, isolines indicate the values of τ_{dust} from CAMS (left panel) and MERRA-
 1631 2 (right panel) reanalysis.

1632 Fig. 6. As Fig. 5, but for 2022-03-15, 12 UTC. The top right panel shows obser-
 1633 vations from MODIS/Aqua. The middle right panel shows forecasts obtained from the
 1634 BSC-DREAM8b model.

1635 Fig. 7. Comparison of the dust frequency in 2021 (left column) and 2022 (right col-
 1636 umn) at 12 UTC from reconstructed images (top) and observations without reconstruc-
 1637 tion (center). The bottom image shows the absolute difference between reconstructed
 1638 and non-reconstructed images in percentage points (pp). For dust plume detection we
 1639 assumed $\Delta E_{\text{cut}} = 51.9$ (see Fig. 3). The respective mean dust occurrence frequency
 1640 is indicated as \bar{f}_{dust} in the panels.

1641 Fig. 8. Comparison of dust occurrence frequency in 2021 from reconstruction with
 1642 different values of ΔE_{cut} (top row) and from CAMS reanalysis with different lower bounds
 1643 of τ_{dust} (middle and bottom row). See Fig. 3 for an interpretation aid of values of ΔE_{cut} .

1644 Fig. 9. Seasonal dust frequency obtained from gray-scaled images with $\Delta E_{\text{cut}} =$
 1645 51.9 (first column, starting from the left) and from reconstructed gray-scaled images (sec-
 1646 ond column). The third column shows the absolute difference between the first two columns.
 1647 For comparison, the occurrence frequency of events with $\tau_{\text{coarse}} \geq 0.65$ as obtained from
 1648 MODIS data is shown in the fourth column. The rows represent the different seasons,
 1649 from top to bottom winter (DJF), spring (MAM), summer (JJA), and autumn (SON).
 1650 See Fig. 3 for an interpretation aid of values of ΔE_{cut} .

1651 Fig. 10. As Fig. 9 but obtained with $\Delta E_{\text{cut}} = 20.0$ and $\tau_{\text{coarse}} \geq 0.9$

1652 Fig. 11. Comparison between reconstructed dust occurrence frequencies at 9, 12,
 1653 and 15 UTC with $\Delta E_{\text{cut}} = 51.9$ (cf. Fig. 3). The left column represents the absolute
 1654 difference between dust occurrence frequencies at 9 UTC and 12 UTC in percentage points
 1655 (pp) and the middle column the absolute difference between 15 UTC and 12 UTC. The
 1656 right column shows the dust occurrence frequency at 12 UTC. The rows indicate the dif-
 1657 ferent seasons. From top to bottom, the rows show the full year, winter (DJF), spring
 1658 (MAM), summer (JJA), and autumn (SON). The black stars in the right column indi-
 1659 cate the location of the Bodélé Depression.

1660 Fig. 12. Comparison of the dust forecasts with respect to the median forecast (blue)
 1661 and with respect to the reconstruction (orange). Colors represent the respective quan-
 1662 tity's distribution. Long dashed black lines represent the median and short dashed black
 1663 lines the first and third quartile respectively. The left column compares forecasts and
 1664 observations for 2021, whereas, the right column shows the comparison for 2022. The
 1665 rows indicate different quality metrics, namely the structural similarity index measure
 1666 (top row), directed Hausdorff distance (middle row), and peak signal-to-noise ratio (bot-
 1667 tom row).

1668 Fig. 13. Comparison of the dust reconstruction with numerical forecasts with by
 1669 the individual models in the ensemble provided by the WMO Barcelona Dust Regional
 1670 Center for 2021 (top row) and 2022 (bottom row). The similarity measures shown are
 1671 SSIM (left column), directed Hausdorff distance (center column), and PSNR (right col-
 1672 umn). As for Fig. 12 the colors show the measures' distributions with long dashed black
 1673 lines representing the median and short dashed black lines indicating the first and third
 1674 quartile. Models marked with * use data assimilation. A full overview of the quartiles

1675 indicated by long-dashed (second quartile) and short-dashed (first and third quartile)
1676 lines is given in Tables S1 and S2.