



HITRA v1.0: An automated workflow for haboob detection and characterization in convection-permitting simulations

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Abstract. Haboobs, dust storms generated by the cold pool outflow from moist convection, are a major dust uplift mechanism, especially over northern Africa in boreal summer. However, systematic model investigations of haboob properties and their contribution to total dust emissions remain limited. Such studies require not only computationally expensive convection-permitting models with an online dust cycle to explicitly simulate haboobs and their associated dust emissions, but also a reliable method to detect haboobs in model output. Here we develop HITRA (Haboob Identification, Tracking and Dust-emission Attribution Algorithm) v1.0, an automated algorithm to detect and characterize haboobs. We apply HITRA to a one-year simulation for 2011 with the Multiscale Online Non-hydrostatic Atmosphere Chemistry model (MONARCH) including online dust at approximately 3 km resolution over North Africa and the Middle East. This allows us to assess both the algorithm performance and the realism of the simulated haboob characteristics. After filtering short-lived events and coastal and orographic artefacts, the diagnostic identified 3,371 haboob events during the simulation year. The resulting event catalogue shows that MONARCH captures key haboob features, including Sahelian hotspots, boreal-summer seasonality, afternoon-to-evening occurrence, mesoscale sizes, and lifetimes of a few hours. Haboobs account for 6.65 % of annual domain-total dust emission and 9.72 % in JJA, with local contributions exceeding 50 % in parts of the Sahel. These results demonstrate that convection-permitting modeling is able to represent haboobs overall realistically and HITRA provides a systematic framework for systematically identifying and characterizing haboobs and quantifying their contribution to dust emissions in convection-permitting simulations.

1 Introduction

Mineral dust is the most important contributor to the total aerosol mass burden (Textor et al., 2006) with diverse impacts across the Earth system and society, including interactions with clouds and radiation (e.g. Shao et al., 2011; Li et al., 2021; Chatziparaschos et al., 2023), nutrient transport to land and ocean ecosystems (Jickells et al., 2005; Westberry et al., 2023), effects on air quality and human health (Stafoggia et al., 2016), and agriculture (Sterk, 2003). Mineral dust is primarily emitted



from arid and semi-arid regions. North Africa contributes most to global mineral dust emissions (Ginoux et al., 2012; Klose et al., 2021; Kok et al., 2021). Dust emission is driven by wind forces, generated through different phenomena such as synoptic-scale systems, low-level jets, and moist or dry convection (e.g. Shao et al., 2010; Knippertz and Todd, 2012; Fiedler et al., 2013; Klose et al., 2016).

Haboobs are intense dust storms caused by cold-pool outflows from moist convection. They are responsible for a significant part of the global dust emissions, with an estimated contribution to summertime dust uplift in parts of the Sahara and Sahel of around 50% (Marsham et al., 2011; Heinold et al., 2013; Garcia-Carreras et al., 2021). Haboobs in North Africa are more likely to form during the summer months, when the Intertropical Discontinuity (ITD) travels northward and monsoonal moisture reaches as far north as the southern Sahara (Marsham et al., 2011). Because convection peaks in the afternoon and evening, haboobs mostly form during this time of day, creating a maximum in the diurnal cycle of dust uplift (Marsham et al., 2011; Heinold et al., 2013; Kocha et al., 2013).

The exact contribution of haboobs to the total dust load is hard to determine. In situ observations are usually sparse in the regions where haboobs occur most frequently, such as in northern Africa. In satellite observations, haboobs are often concealed by clouds (Heinold et al., 2013; Kocha et al., 2013). Modeling studies of haboobs also remain limited so far. At horizontal model grid spacings of more than about 10 km, convection cannot be represented explicitly and parameterizations need to be used. In such simulations, haboobs are largely absent, which leads to an underestimation of dust uplift for regions where haboobs are prominent (Pope et al., 2016). It also leads to difficulties in reproducing the observed diurnal and seasonal cycles of dust uplift, which is impacted by the presence of haboobs (e.g. Marsham et al., 2011; Garcia-Carreras et al., 2021). Simulations with horizontal grid resolutions of only a few kilometers, so-called convection-permitting or storm-resolving simulations, are able to explicitly resolve the moist convective processes responsible for haboob formation (Heinold et al., 2013; Pantillon et al., 2015; Segura et al., 2025). However, simulations at such resolutions are computationally costly and have therefore, until recently, mostly been limited to small spatial domains, short simulation periods, and/or setups without online computations of dust emission and transport (Vukovic et al., 2014; Pantillon et al., 2015; Roberts et al., 2018). Including online dust emission and transport further increases computational expense. Therefore, analyses based on such simulations have typically relied on wind-based proxies to estimate dust emissions (e.g. Heinold et al., 2013; Garcia-Carreras et al., 2021). Enhanced computing capabilities and model infrastructure now allow to conduct larger-scale convection-permitting simulations including online dust cycle computations. This paves the way for a more detailed model investigation of haboobs. Exploiting these simulations, and evaluating how realistically they represent haboobs, requires a reliable method to identify and track individual events.

In this paper, we introduce HITRA (Haboob Identification, Tracking and Dust-emission Attribution algorithm) v1.0, an automated diagnostic framework that identifies haboobs, tracks their temporal evolution, and attributes dust emissions to them, so that their properties can be quantified. We use HITRA to analyze a one-year convection-permitting simulation of North Africa and the Middle East with online coupled dust, performed with the Multiscale Online Non-hydrostatic Atmosphere Chemistry (MONARCH) model (e.g. Pérez et al., 2011; Jorba et al., 2012; Badia et al., 2017; Klose et al., 2021; Gonçalves Ageitos et al., 2023). The derived haboob properties are evaluated statistically against observations to assess both the ability of MONARCH to reproduce key haboob characteristics and the applicability of HITRA for haboob identification and characterization.



2 Convection-permitting model simulation

The MONARCH model is used for chemical weather modeling and undergoes continuous development at the Barcelona Supercomputing Center (BSC), e.g. related with aerosols and mineral dust (e.g. Klose et al., 2021; Escribano et al., 2023; Gonçalves Ageitos et al., 2023) or atmospheric chemistry (e.g. Soussé-Villa et al., 2024; Oliveira et al., 2024). The entire dust cycle (dust emission, advection, transport, dry and wet deposition) is represented in MONARCH as described in Klose et al. (2021).

An annual simulation for the year 2011 was conducted with MONARCH at a resolution of 0.025° (approximately 3 km) in longitudinal and latitudinal direction with a rotated pole longitude-latitude grid for a domain covering northern Africa and the Middle East (see Fig. 1). This resulted in more than 4 million (3201×1301) grid points at each horizontal level. In the vertical direction, 60 layers were used. The computational time step was 5 s and the output time interval was 1 h. Convection was explicitly represented in the simulation.

ERA5 reanalyses (Hersbach et al., 2020) were used as initial and boundary conditions. MONARCH was run consecutively for 36 h time periods, initialized daily at 12 UTC. The first 12 h were used as spinup and were not used for the analysis, such that the full year was obtained from individual simulations combined daily at 00 UTC. The dust fields and soil moisture were transferred between each individual run. For soil moisture, an 11 months spinup was run at 0.1° resolution and a one month spinup was used for soil moisture and dust at the final resolution. Turbulence, surface layer, dust emission, sedimentation, and dry deposition routines were called every four computational time steps, whereas moist convection, microphysics and wet scavenging routines were called every eight time steps. The short- and longwave radiation routines were called every 80 time steps.

We applied the dust emission scheme from Shao (2004), which estimates dust emission from the soil volume removal caused by saltation. The scheme was implemented as described in Klose et al. (2021). Here we used the soil moisture correction on the threshold friction velocity from Klose et al. (2014) based on Shao and Jung (2000, unpublished). Additionally, a scaling factor of $c_{f_1} = 0.1$ was applied to soil moisture (Klose et al., 2021). The drag partition parameterization of Raupach et al. (1993) was employed to account for the impact of surface roughness on the friction velocity. It relied on input for photosynthetic and non-photosynthetic vegetation cover from MODIS and Landsat surface reflectance (Guerschman et al., 2015; Klose et al., 2021). Potential dust source areas were defined in a binary sense. They were based on the frequency of occurrence (FoO) of MODIS dust optical depth (DOD) greater than 0.2. If the FoO was greater than 0.025, the area was considered as a potential dust source. In MONARCH, dust emissions were calculated in eight size bins from $0.2\mu\text{m}$ to $20.0\mu\text{m}$. The dust variables were calibrated using a global calibration factor of 0.36 derived from a comparison of the monthly and domain averaged DOD with the DOD obtained from MODIS Deep Blue (Hsu et al., 2004; Ginoux et al., 2012).

3 Haboob identification, tracking and dust-emission attribution

To characterize haboob dust storms and their properties in the MONARCH simulation, we develop HITRA v1.0. This algorithm first detects model haboob leading edge grid points and clusters them into individual haboobs at each time step. Haboob



clusters identified at consecutive time steps are then connected if they are considered to belong to the same haboob based on the approximate travel speed of the haboob. The tracked haboobs are subsequently filtered to remove detections associated with coastlines, topography, and short-lived events. Finally, the cold pool region associated with each haboob is identified to attribute dust emissions to haboobs. The individual steps are described in more detail in the following subsections.

3.1 Haboob identification and tracking

3.1.1 Identification of haboob leading-edge grid points

We used the criteria from Pantillon et al. (2015, 2016), which followed Heinold et al. (2013), to identify cold pool leading edges in the model data. This identification method is based on the anomaly in the temperature tendency relative to the mean diurnal cycle, $(\dot{T} - \dot{T}_{\text{avg}})$, and on the vertical wind velocity w , both obtained from the model output. For this purpose, temperature T and vertical velocity w were interpolated to specific pressure levels with a cubic spline (Ahlberg et al., 2016). As in Pantillon et al. (2016), T was taken from the model at the 925 hPa pressure level, and w was taken at the 850 hPa level. The temperature tendency $\dot{T}$ is the time derivative of T . Its anomaly was calculated in comparison to the five-day centered average of the diurnal cycle in temperature tendency $\dot{T}_{\text{avg}}$. The thresholds for haboob leading edge identification were set to

$$(\dot{T} - \dot{T}_{\text{avg}})_t = -1 \text{ K h}^{-1} \quad (1)$$

for the anomaly in temperature tendency and

$$|w|_t = 0.5 \text{ m s}^{-1} \quad (2)$$

for the absolute value of vertical velocity. The threshold for the vertical velocity needs to be adapted according to the grid resolution. For finer resolution, a model can produce larger vertical velocities. As the grid resolution in our simulation was similar to that used in Pantillon et al. (2015) (3 km vs. 4 km), we applied the same threshold of 0.5 m s^{-1} .

These two meteorological criteria are sufficient only to detect cold pool outflows from moist convection, which are a pre-requisite for haboobs. Storms identified in this way may or may not carry dust, as the model domain is large enough to include both dust source regions and regions where dust uplift is unlikely due to, e.g., vegetation. To identify haboobs as those cold pool outflows that do carry dust, a normalized surface dust concentration tendency criterion was applied. The threshold was set to

$$\left(\frac{\dot{C}_{\text{dust}}}{C_{\text{dust}}} \right)_t = 0.5 \text{ h}^{-1}, \quad (3)$$

where C_{dust} is the surface dust concentration and $\dot{C}_{\text{dust}}$ is the time derivative of C_{dust} . The normalization with C_{dust} accounts for regional variations in dust intensity, ensuring that haboob grids are detected consistently across different geographical areas. This approach is required for future global-scale detection.

Fig. 1 shows an example of all three identification criteria (Figs.1a–c) and the resulting identified grid points (Fig.1d) at 18 UTC on 4 June 2011. Due to the dust tendency criterion, many of the southernmost points that satisfied the vertical velocity and temperature tendency anomaly criteria, i.e., the points near 8°E , 10°N , were not identified as haboob grid points.

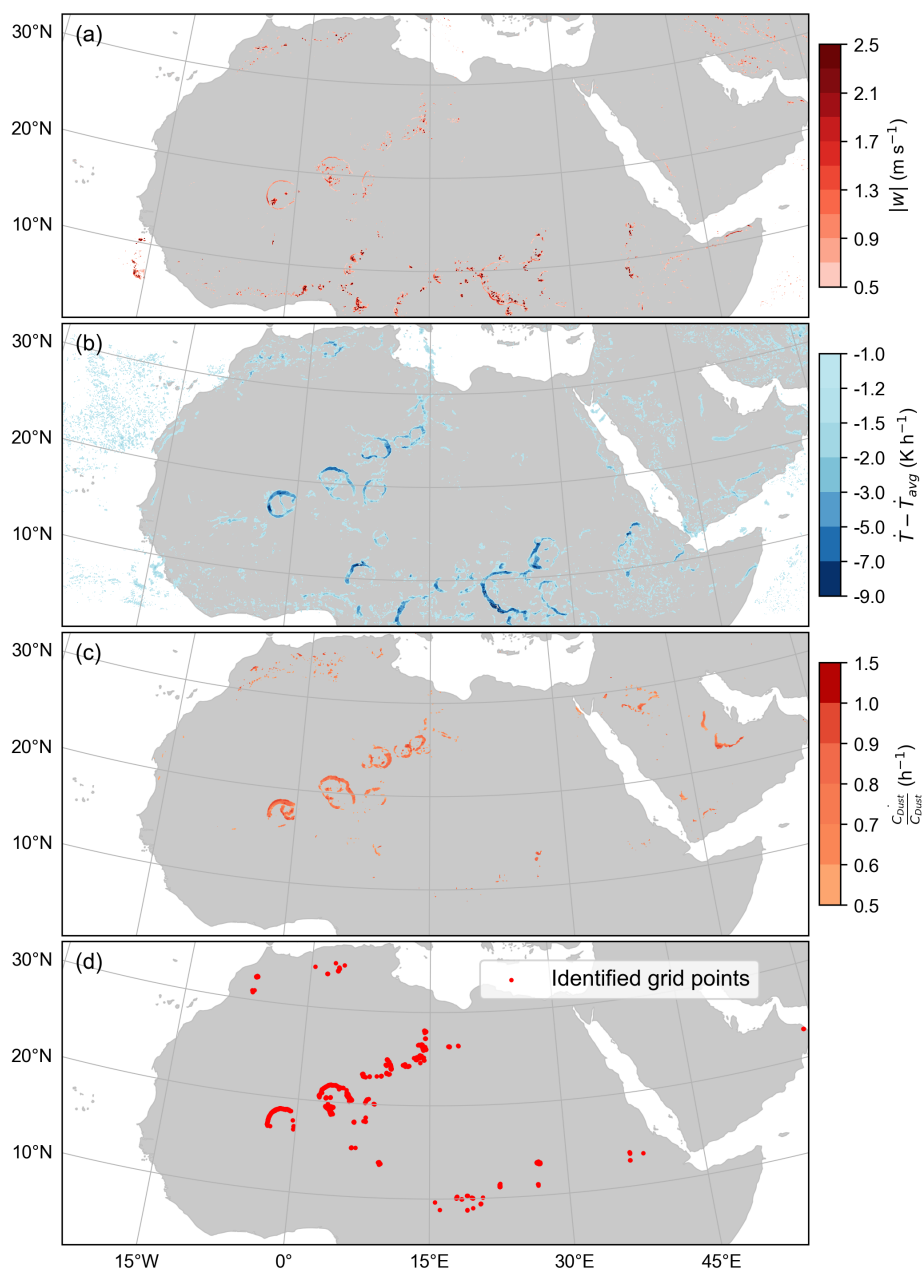


Figure 1. Comparison of the three haboob leading edge identification criteria: (a) vertical velocity $|w|$, (b) temperature tendency anomaly $\dot{T} - \dot{T}_{\text{avg}}$, and (c) normalized surface dust concentration tendency $\frac{\dot{C}_{\text{dust}}}{C_{\text{dust}}}$. Panel (d) shows the haboob leading edge grid points identified based on the criteria displayed in (a)–(c). The snapshot is taken for 4 June at 18 UTC.



3.1.2 Spatial clustering of identified leading-edge grid points

The haboob leading edge grid points identified as described in Sec. 3.1.1 are independent of each other. To spatially connect them into individual haboobs, the clustering algorithm DBSCAN (Density-Based Spatial Clustering of Applications with Noise) was applied. This algorithm uses two parameters: epsilon (ϵ), which defines the radius of the neighborhood around a point, and the minimum number of points (N_{minPts}) required within this neighborhood for a point to be considered part of a dense region (Ester et al., 1996; Schubert et al., 2017).

To eliminate small-scale systems such as microbursts, spatial clustering was conducted in two steps. First, a smaller epsilon ($\epsilon = 5$, approximately 15 km) was applied to remove small-scale noise. Points that did not satisfy the density requirement within this small radius, such as isolated points or small, loosely grouped clusters, were classified as noise and excluded. In the second step, a larger epsilon ($\epsilon = 25$, approximately 75 km) was used to group the remaining haboob leading edge grid points into spatially connected clusters. This approach was based on the typical size of haboobs, which ranges from tens to hundreds of kilometers (Roberts and Knippertz, 2014; Miller et al., 2008). The ϵ values were fine-tuned to obtain physically reasonable clustering results, such that individual haboob systems are represented as coherent structures without being artificially split into multiple fragments (too small ϵ) or incorrectly merged with nearby systems (too large ϵ). For $\epsilon = 25$, N_{minPts} was set to 6, meaning that at least six points clusters were required within the ϵ neighborhood to form a dense region; otherwise, the points were classified as noise. Given the model grid size of 3 km, a cluster of six grid points corresponds to a spatial scale on the order of 10 km, representing the lower bound of typical haboob sizes (Miller et al., 2008). For $\epsilon = 5$, N_{minPts} was set to 2. The clustering results are illustrated in Fig. 2, where different colors represent different haboobs. To simplify the calculations, the clustering algorithm was applied directly on the rotated pole grid coordinates used in MONARCH. In our case, this approach did not lead to significant changes in the clustering results compared to using geographical distances. However, for simulations with different configurations, this may need to be adapted accordingly.

3.1.3 Temporal tracking of haboob events

After clustering the identified haboob leading edge points in space separately at each time step, the resulting clusters were temporally connected across consecutive time steps to identify those belonging to the same haboob. For this purpose, clusters were connected forward in time using a distance criterion. If a point belonging to cluster B at hour $n + 1$ was located within about 40 km of any point in cluster A at hour n , clusters A and B were assumed to belong to the same haboob and assigned a common label (shown by a common color in Fig. 2). With this approach, if a haboob splits into multiple parts, all parts are considered to belong to the same haboob. The 40 km distance threshold was chosen considering a propagation speed of approximately 10 m s^{-1} at the haboob leading edge (Kalenderski and Stenchikov, 2016; Caton Harrison et al., 2021). With an output interval of one hour, this corresponds to a travel distance of about 40 km. This process was repeated for all time steps during one day. Due to the daily model re-initialization, haboobs could not be connected across days.

In situations where two or more haboobs merged into one, all parts are likewise identified as belonging to a single haboob even before the merging process happened. For this purpose, the same temporal connection procedure as before was applied

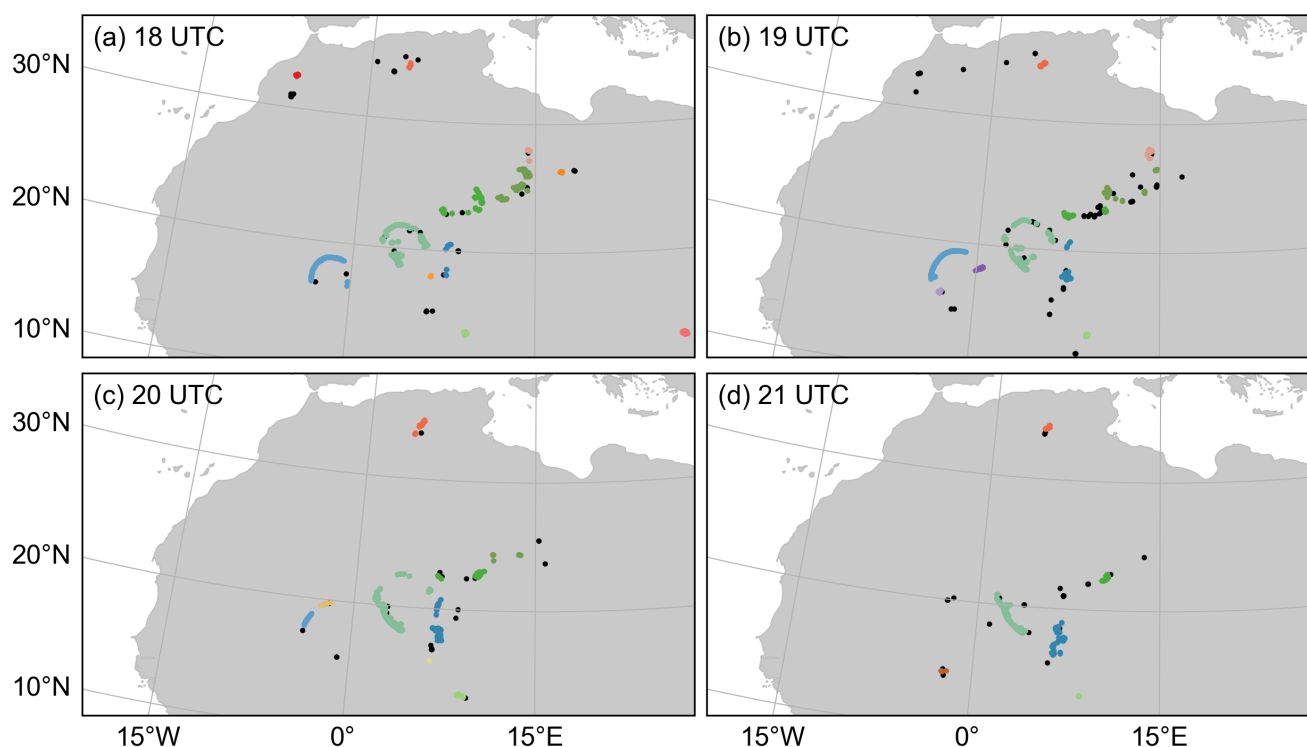


Figure 2. Results after applying the clustering algorithm to identified leading edge grid points of haboobs and connecting the clusters in time. Shown are leading edges of haboobs for 4 June 2011 at (a) 18, (b) 19, (c) 20 and (d) 21 UTC. Each haboob (composed of a cluster of identified leading edge points) is depicted in a different color, whereas noise is represented by black dots.

to the data once more, but backwards in time, such that clusters were compared with clusters in the subsequent hour instead of
155 the previous hour. After obtaining the results of the forward and backward temporal connection algorithms, both results were
combined in a final step. For clusters where two approaches yielded different labels, which only occurred in cases of splitting or
merging, a size-based criterion was applied. Specifically, the cluster (from either approach) containing a larger number of grid
points was retained, and all associated parts were assigned a common label. This procedure ensured a consistent representation
of haboob splitting and merging. After this step, each haboob leading edge was assigned a unique identifier for its entire
160 lifetime.

Note that merging and splitting leading edges were retained as part of the same tracked haboob structure, rather than being
assigned separate identities. This treatment follows the event-based tracking approach adopted here. Alternative treatments
may be adopted for applications requiring explicit representation of merging and splitting.



3.1.4 Event filtering and diagnostics

165 Following the identification and tracking procedure, three filters were applied to remove false detections associated with coastlines, pronounced topography, and short-lived signals.

Signals associated with coastlines and topography were often persistent and could therefore bias the statistics of identified haboobs. To exclude coastal signals, a coastal buffer zone was defined using the binary erosion technique by extending 20 grid points (approximately 54 km) inland from the coastline. This distance is consistent with the typical inland penetration range
170 of sea-breeze circulations (about 50–100 km) in this region (Davis et al., 2019; Pedgley, 1974). Grid points within this buffer were identified as coastal grid points. Identified events were removed if they occurred at a coastal grid point during at least one of the first two time steps and one of the last two time steps of their lifetime. A similar procedure was applied to signals associated with pronounced topography. Grid points with an altitude above 2000 m were identified. An event was discarded when its leading edge occurred over such grid points during at least one of its first two time steps and at least one of its last
175 two time steps. By combining these two filters, signals associated with land sea breeze and mountain valley breeze circulations were no longer identified as haboobs.

In addition, a considerable number of haboob signals were found to persist only for short periods, leading to an unrealistically large total number of detected haboobs. Therefore, short-lived haboobs with a lifetime of less than 2 h were filtered out. The same filter for short-lived haboobs was also applied by Caton Harrison et al. (2021).

180 After filtering, the direct output of the haboob identification and tracking procedure is a tracked leading-edge grid-point catalogue. Each record corresponds to one identified leading-edge grid point at one time step and contains the time, grid longitude index, grid latitude index, and event identifier. These outputs provide the basis for subsequent analyses of the spatial and temporal characteristics of haboob occurrence, including occurrence frequency, seasonal variability, and the diurnal cycle (Secs. 4.1–4.2).

185 From the grid-point event catalogue, we further derived event-level diagnostics for each identified haboob, including its initiation time, lifetime, and maximum size over its lifetime. The initiation time was defined as the first time step at which the haboob was identified. Because the model domain spans several time zones, initiation time was expressed in local time to better relate haboob activity to the diurnal cycle of solar insolation and convection. For this purpose, the centroid of the leading-edge grid points was calculated at the initiation time step, and the local time of the event was determined from the longitude-based
190 local time (LLT) at the centroid location. The event lifetime was determined as the time interval between its first and last detected occurrences. Due to the simulation design (daily re-initialization), haboobs could only be tracked continuously within individual simulation days. The maximum resolvable haboob lifetime in our setup was therefore 24 h, although haboobs may persist for longer than one day in reality.

The size of a haboob is defined as the distance between the two most distant points of its leading edge. As the haboob
195 size varies with time, here we analyzed the maximum size of a haboob during its lifetime. When multiple leading edge parts belonging to the same haboob occurred at a given time step (e.g., due to splitting or merging), the size of each part was calculated separately. The size of the haboob at that time step was then defined as the maximum of these individual parts. This



approach avoids unrealistically large sizes that may arise when distant leading edge segments are temporarily associated with the same haboob by our connection method.

200 The complete haboob identification and tracking workflow is summarized in Fig. 3a.

3.2 Dust-emission attribution

The procedure described in Sect. 3.1 identifies haboob leading edges but does not capture the full storm structure. However, attributing dust emissions to individual haboobs requires identifying all grid points belonging to the same system. To achieve this, we applied a K-Means clustering method to identify the whole cold pool region associated with the detected leading edge points (Hirt et al., 2020; Gentile et al., 2016).

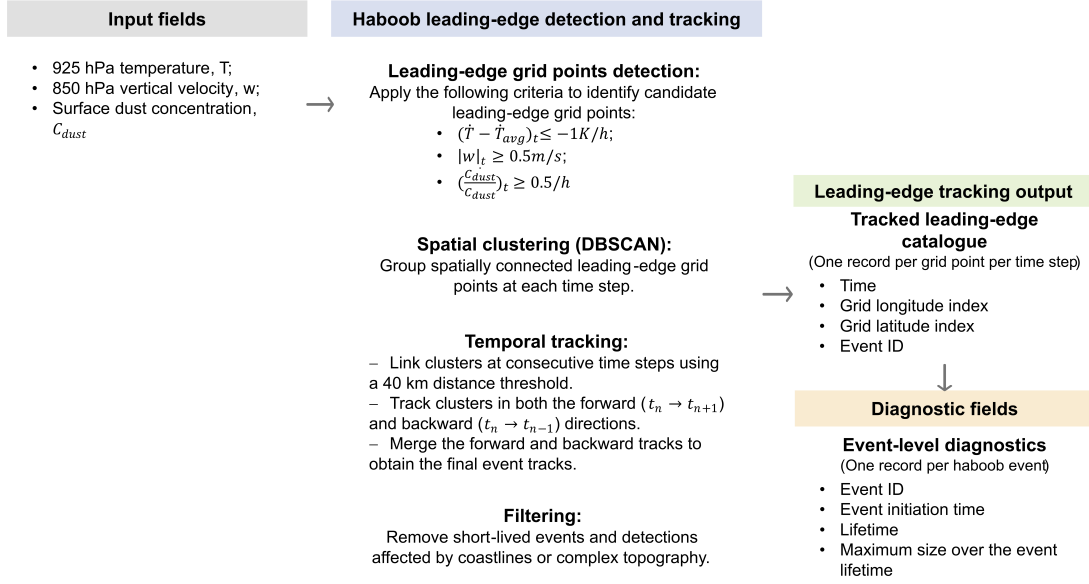
First, the original thresholds used to identify haboob leading edges may be too restrictive during the initiation or dissipation stages of a storm, such that only a fraction of the leading edge is identified (e.g., black dots in Fig. 4). Figure 4 shows the same haboob event as Fig. 1, but at a later stage (21 UTC), when only part of the leading edge satisfies the original thresholds, to better illustrate this situation. The detected leading edges were therefore extended to better represent the full haboob structure. For this purpose, relaxed thresholds (light shading in Figs. 4a–c) were applied to the grid points adjacent to the initially detected edges: $|w|_t \geq 0.1 \text{ m s}^{-1}$, $(\dot{T} - \dot{T}_{\text{avg}})_t \leq -0.5 \text{ K h}^{-1}$, $\left(\frac{\dot{C}_{\text{dust}}}{C_{\text{dust}}}\right)_t \geq 0.2 \text{ h}^{-1}$. Note that the extended leading edge points were used only to identify the cold pool region associated with each haboob. They were not used in the subsequent analysis of haboob properties because this relaxed approach produced a lot of false detections during the developing and mature stages of the storms.

215 Next, the cold pool region was identified at each time step using K-Means. The clustering features used for K-Means were surface friction velocity and the 925 hPa virtual potential temperature (T_v) anomaly, which was defined as an anomaly relative to a five-day centered mean. These two variables were selected since they can capture both the dynamical (enhanced near-surface winds) and thermodynamical (cold air) characteristics of cold pools (Engerer et al., 2008). Before clustering, both features were spatially smoothed using a 180 km convolution kernel, which lies within the typical haboob size range (Miller et al., 2008) and was chosen to obtain robust clustering results (Figs. 5a,b). Only land grid points were included in the analysis; ocean grid points were masked out. The data were then partitioned into three clusters (Fig. 5c), and the cluster with the lowest T_v was identified as the cold clusters (Fig. 5d), while the remaining clusters were classified as the environment. Three clusters were used instead of two because a two-cluster configuration produced more false detections. The cold cluster was further separated into individual systems with a watershed algorithm and only those systems connected to previously extended leading edge grid points were retained (Fig. 5e). Finally, a morphological dilation was applied to fill small gaps and obtain a smoother representation of the cold pool structure (Fig. 5f). Dust emissions occurring within the identified cold pool region were attributed to the corresponding haboob. The resulting output is a gridded cold-pool mask for each time step, containing the time and grid-point indices of the regions associated with haboobs. The complete cold-pool identification and dust-emission attribution workflow is summarized in Fig. 3b.

230 Figure 6 shows the distributions of T_v anomaly, surface friction velocity, and hourly emitted dust for an example haboob event. Compared to the surrounding environment, the haboob region exhibited a colder T_v anomaly and enhanced surface fric-



(a) Haboob leading-edge detection and tracking



(b) Cold-pool identification and dust attribution

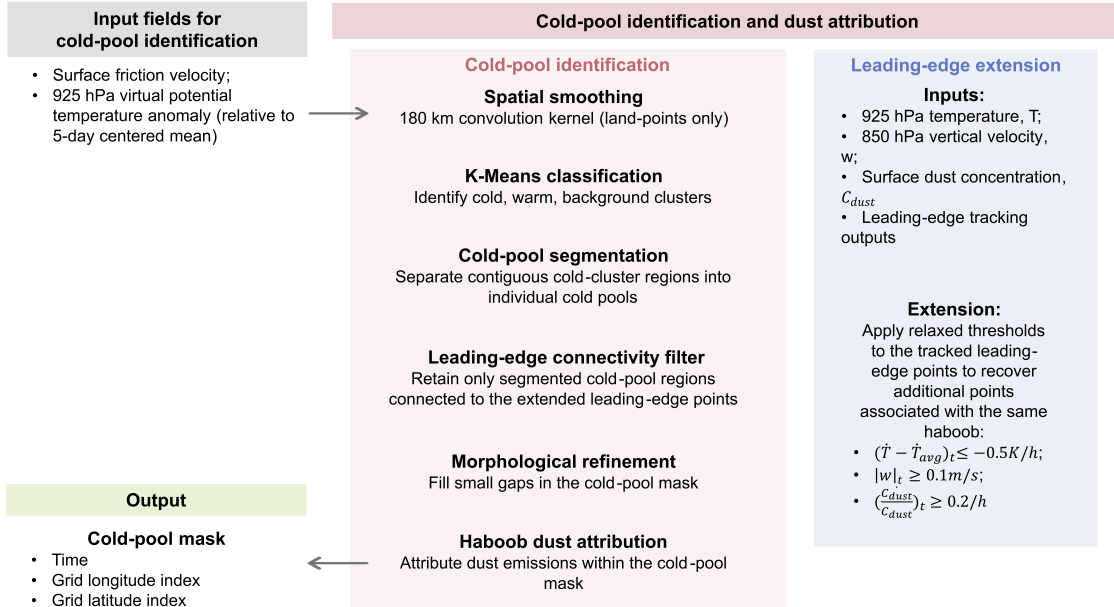


Figure 3. Schematic overview of the Haboob Identification, Tracking, and Dust-emission Attribution (HITRA) framework. (a) Identification and tracking of haboob leading edges, producing a tracked grid-point event catalogue from which event-level diagnostics are subsequently derived. (b) Identification of haboob-associated cold pools and attribution of dust emissions using the tracked leading-edge information from panel (a).



tion velocity (Figs. 6a–b). These contrasting dynamical and thermodynamical signatures support the use of K-Means clustering to objectively distinguish the cold pool from the environment. The gray shading in Fig. 6c indicates the identified cold pool region. Although the identified cold pool region extended beyond the identified leading edge grid points, its spatial content corresponded well with the surface convergence pattern, indicating that the identified region was physically reasonable. One thing to note is that dust emissions output from the model are cumulative values between consecutive output intervals (here over each hour), rather than instantaneous values at a specific time step. As haboobs generally do not stay at the same place during the entire hour, this may lead to small errors in the obtained dust emissions caused by haboobs.

4 Haboob occurrence and properties

Using the algorithm described above, we analyzed the times and locations of haboob occurrences as well as key haboob properties, such as their lifetime, size, and contribution to total dust emission.

4.1 Spatial distribution of haboob occurrence

To determine the spatial distribution of haboob occurrences, the number of haboob leading edge passages was calculated at each grid point. One leading edge passage was defined as a detection at a grid point at one hour, no matter to which haboob it belongs. Figure 7a shows the number of all haboob leading edge passages in 2011. Note that due to a technical issue with model output data for 21 March 2011, this day is missing from all model analyses. The main haboob hotspots for the entire year were located in Mali and the western part of Niger. Strong and very localised signals were also visible along the Red Sea coast, the Atlas mountains, and southwestern Iran. These signals were likely not related to haboobs. The signals along the Red Sea coast can be attributed to the land sea breeze circulation in combination with the coastal topography. Similarly, signals along mountain ranges can be explained with the mountain valley breeze circulation.

Figure 7b shows the number of haboob leading edge passages after applying filters for short-lived haboobs and haboobs associated with coastlines and pronounced topography, while Fig. 7c depicts the number of passages specifically caused by short-lived haboobs and by coastline and topography effects. Compared to Fig. 7a, the signals in elevated areas and near coastlines became weaker. The following analysis will be conducted based on the filtered results unless otherwise specified. As shown in Fig. 7b, haboobs mostly occurred in the Sahel region. Beyond the two main haboob hotspots in Mali and Niger, weaker hotspots were observed in eastern Chad, near the western border of Sudan and southwestern Eritrea. Haboobs also occurred in western Sahara and the Rub' al Khali desert on the Arabian peninsula.

Figure 8 shows the number of haboob leading edge passages per grid point for each season to gain insight into the haboob seasonal cycle. As expected, December, January and February (DJF) exhibits the lowest haboob activity. During March, April and May (MAM), the ITD travels northward and haboob activity increases. The main hotspots during this period were located in western North Africa and the northeastern part of the Arabian peninsula. In June, July and August (JJA), haboob activity reached its peak. Compared to MAM, when large parts of the domain exhibited a similar number of leading edge passages of between 1 and 4, regions with pronounced activity identified also in the annual analysis, i.e. Mali, Niger, Chad, and the south-

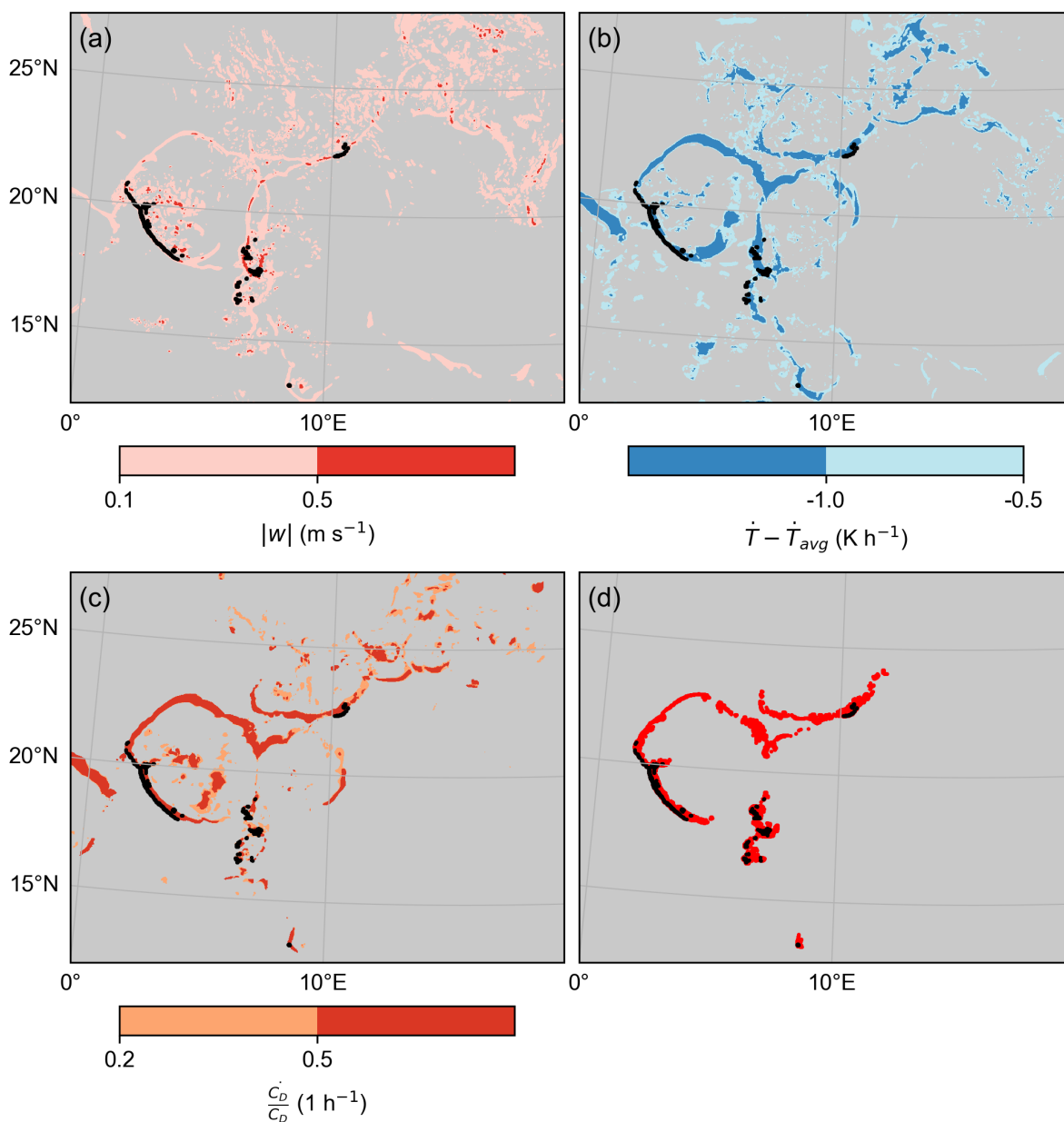


Figure 4. As in Fig. 1, but for a zoomed-in subregion at 21 UTC with adjusted color scales to illustrate the leading-edge extension procedure. Light shading in (a)–(c) indicates grid points that satisfy the relaxed threshold but not the initial threshold, whereas darker shading indicates grid points that meet the initial stricter threshold. Black dots in (a)–(d) represent the identified leading edge grid points based on the initial criteria, while red dots in (d) indicate the additional grid points included by the extension procedure.

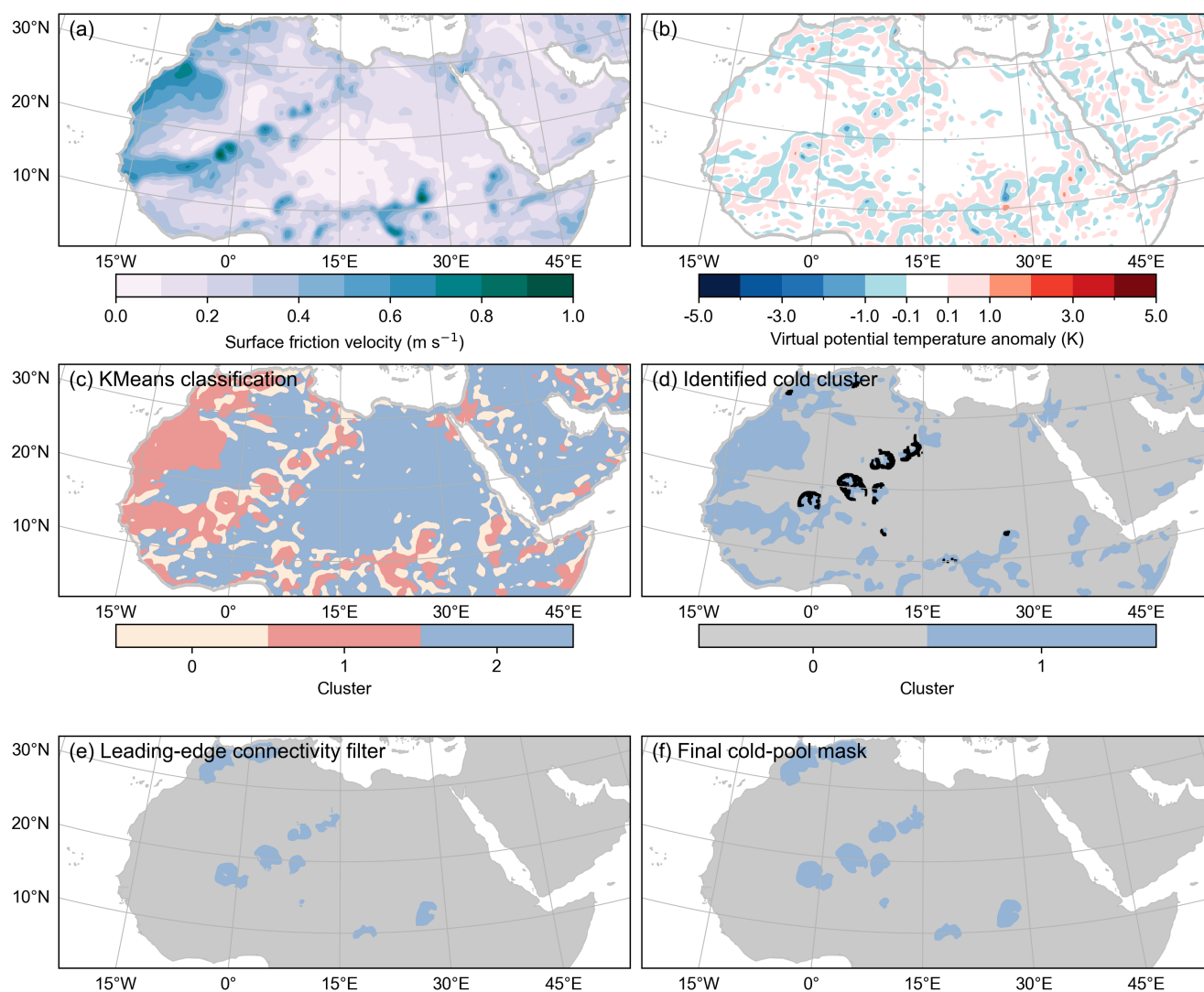


Figure 5. Spatial distributions of (a) surface friction velocity and (b) virtual potential temperature anomaly, which were used as clustering features. (c) K-Means classification results. (d) Identified cold cluster, with black dots indicating the extended haboob leading edge points. (e) Cold-pool systems retained after watershed segmentation and connectivity filtering. (f) Final identified cold-pool mask after morphological dilation. The snapshot corresponds to the same time as in Figs. 1 and 2a.

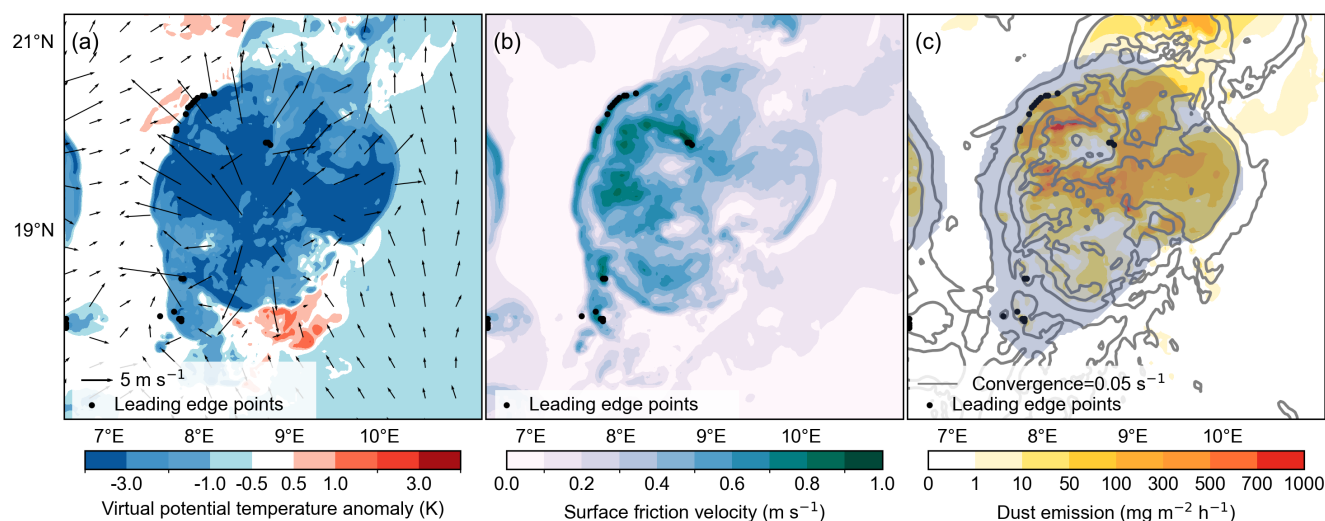


Figure 6. Spatial distributions of (a) virtual potential temperature anomaly, (b) surface friction velocity, and (c) hourly emitted dust for an identified haboob at the same time as in Figs. 1, 2a, and 5. The vector in (a) indicates 10 m wind fields. The gray contour in (c) shows the isoline of surface convergence at 0.05 s^{-1} . The gray shading in (c) depicts the cold pool region associated with the identified haboob leading edge as described in Sec. 3.2. The black dots in (a)–(c) represent the identified haboob leading edge points.

eastern Arabian peninsula, stand out. Activity in the northeastern Arabian peninsula and the northwestern Sahara decreased substantially. Caton Harrison et al. (2021) detected a hotspot of haboob activity in JJA near the Mali-Niger-Algeria boarder triangle, located at around 4°E , 20°N . A similar hotspot, slightly further west, can also be found in our model results, indicating the effectiveness of our detection method. Haboob activity declined again in September, October and November (SON) across all regions.

4.2 Temporal distribution of haboob occurrence

Throughout the year, 18,940 haboobs were identified including short-lived signals and signals related to topography or coastlines. This number seems unrealistically high. After filtering out short-lived haboobs, the number was reduced to 3,777. When signals in mountainous and coastal regions were additionally removed, the number further decreased to 3,371. In Caton Harrison et al. (2021), 1,559 haboob events were detected in satellite data over the central and western Sahara during JJA for the years 2004 to 2017, corresponding to an average of 111.4 events per summer season. When considering haboobs only in JJA and in the same area as in Caton Harrison et al. (2021), we identified 483 haboobs with all filters applied. This is roughly four times the average number per summer season reported from satellite data. Several factors may explain this discrepancy. One possible reason is the underestimation in satellite-based detection due to cloud shading and concealment effects. Besides, despite the applied filtering, some false signals near the coastlines or mountain ranges may still remain in our results. Further-

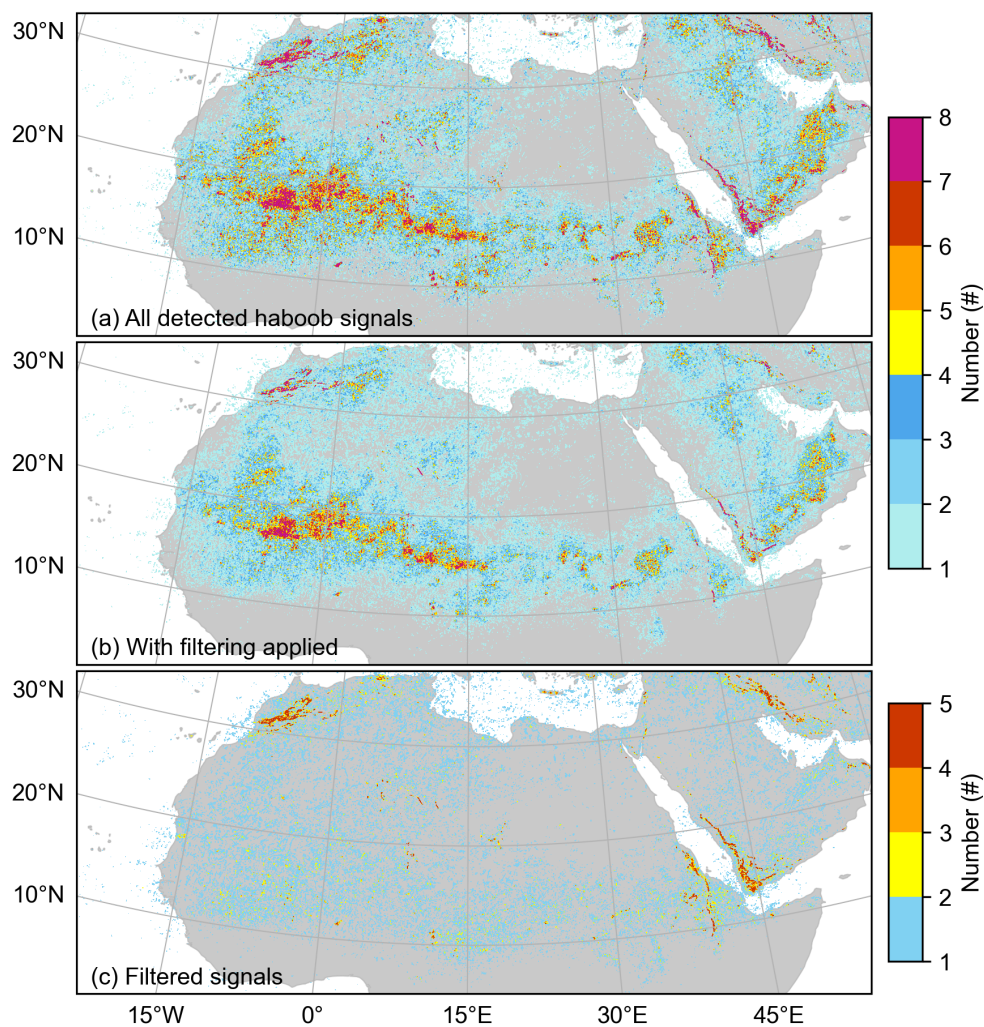


Figure 7. Annual number of haboob leading edges passages during the 2011 simulation for (a) all detected haboob signals, (b) signals after removing coastline and topography effects and short-lived haboobs, and (c) signals removed by these filters. Note that the color scale in (c) differs from that in (a)–(b).

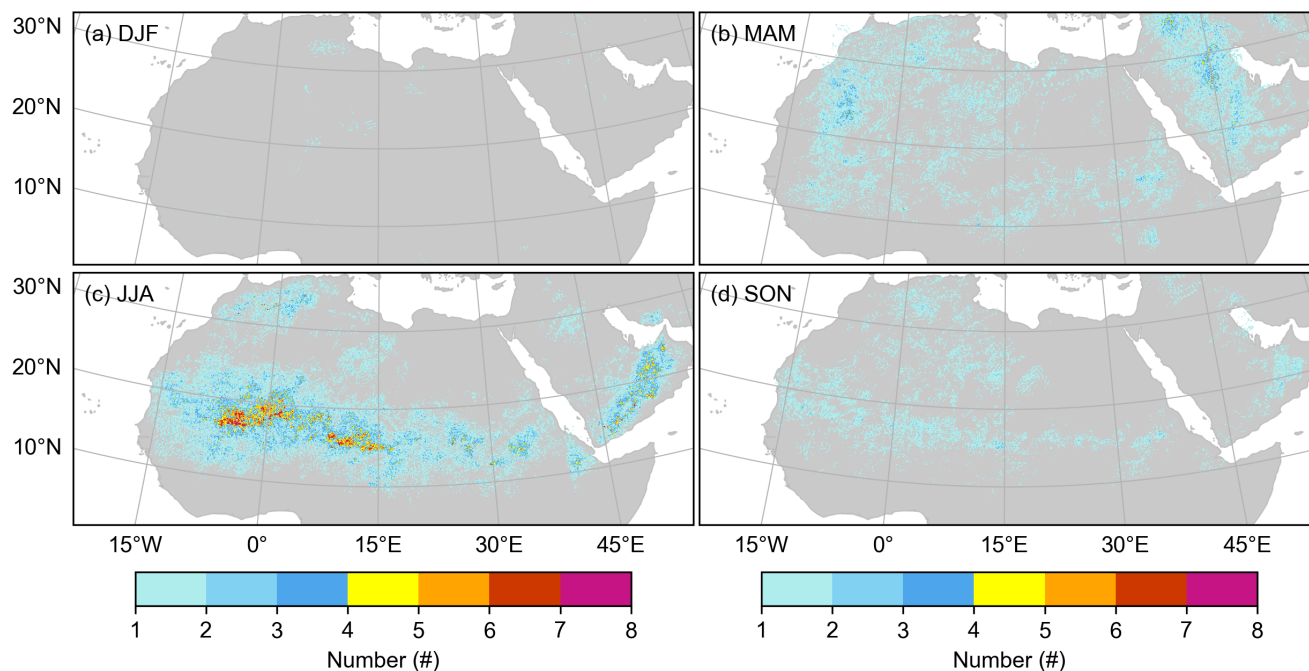


Figure 8. As in Fig. 7b, but for (a) December, January, and February (DJF), (b) March, April, and May (MAM), (c) June, July, and August (JJA), and (d) September, October, and November (SON).

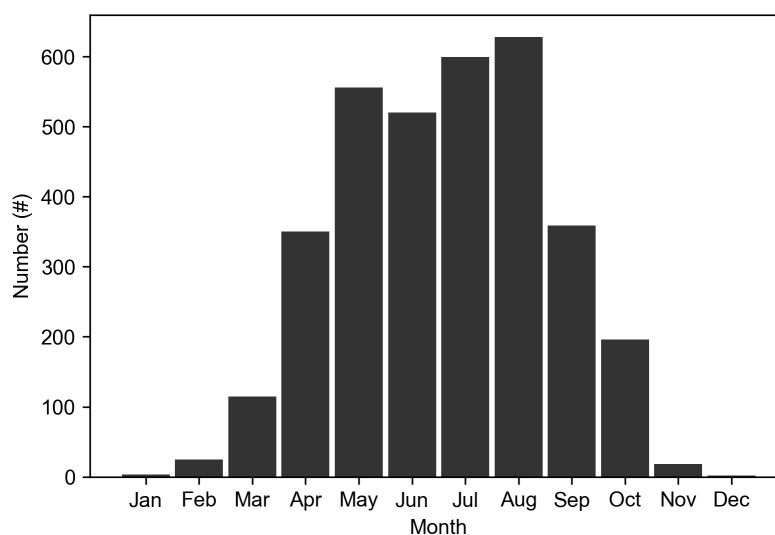


Figure 9. Seasonal cycle of haboob occurrence during the 2011 simulation. Bars show the monthly number of identified haboob events over the entire model domain, with each haboob counted once.



more, haboobs that would normally persist from one day to the next may be split into separate events in our simulation due to the daily model re-initialization. Both aspects may have led to a slight overestimation of the number of haboobs in our results.

Figure 9 shows the number of haboobs for each month. As expected and consistent with the seasonal cycle of haboob passages (Fig. 8), haboob activity increased during the warmer months. The largest number of haboobs (628 events) occurred in August, followed by July, May, and June (599, 556, 520 events, respectively). The smallest numbers of haboobs were found in January and December. The peak in May is likely associated with upper-level troughs originating from the mid-latitudes, which promote convection over the Atlas mountains and northwestern Sahara. The August peak corresponds to the monsoon maximum, after which haboob activity rapidly declined with the retreat of the monsoon in September (Knippertz et al., 2007; Pantillon et al., 2016). Interestingly, there was a decrease in haboob activity in June, despite expectations of a peak due to the monsoon onset (Pantillon et al., 2016). This discrepancy may be related to the simulated timing of the monsoon onset in the model; however, this hypothesis needs further investigation.

We also investigated the diurnal cycle of haboob occurrence for JJA, as the diurnal cycle of insolation and, consequently, convection was expected to be most pronounced during this time period. For this purpose, we first determined the hourly haboob occurrence for each day separately. To account for the different time zones across the model domain, the occurrence time of each haboob at every time step was converted from UTC to LLT using the longitude of the haboob centroid at that time step, following the procedure described in Sect. 3.1.4. The average diurnal cycle was then calculated over all days in JJA. The results are shown in Fig. 10, which depicts a pronounced diurnal variation in haboob occurrence (black line), with large differences between morning and afternoon hours. The maximum number of haboobs occurred at 17 LLT after a steep increase. Haboob numbers then declined during the nighttime hours and reached their minimum in the morning at 09 LLT.

In addition to the number of haboobs present at a given time, we also quantified the number of haboob generations. For this purpose, the event initiation time derived in Sect. 3.1.4 was used, such that each haboob was counted only once. Figure 10 shows that, as expected, the increase in haboob generations was slightly ahead of that in haboob occurrence, with a peak at 14 LLT (red line). The large value in the first hour is due to the model re-initialization, which means that at 01 UTC all haboobs were identified as new signals. This leads to an overestimation of haboob generations during the first hours (in LLT) of the day. Based on satellite data, Caton Harrison et al. (2021) found a peak in the diurnal cycle of haboob generation (defined as the time step of first detection) between 17 and 19 UTC. However, the authors expected the true outflow production to appear earlier, which is consistent with our results.

4.3 Haboob lifetime and size

The identified haboob events were further characterized using the derived event diagnostics, including lifetime and maximum size. The number of haboobs identified with a given lifetime declined exponentially with increasing lifetime (Fig. 11a). A similar number of haboobs occurred with lifetimes of 10–11 h, followed by a stronger decline for lifetimes between 12 and 15 h. The median lifetime was 3 h. Allen et al. (2015) determined the lifetimes of 21 (39) haboobs observed at Bordj-Badji Mokhtar in June 2011 (2012). They obtained median lifetimes of 1 h (4.5 h), while the longest-lived haboob observed lasted

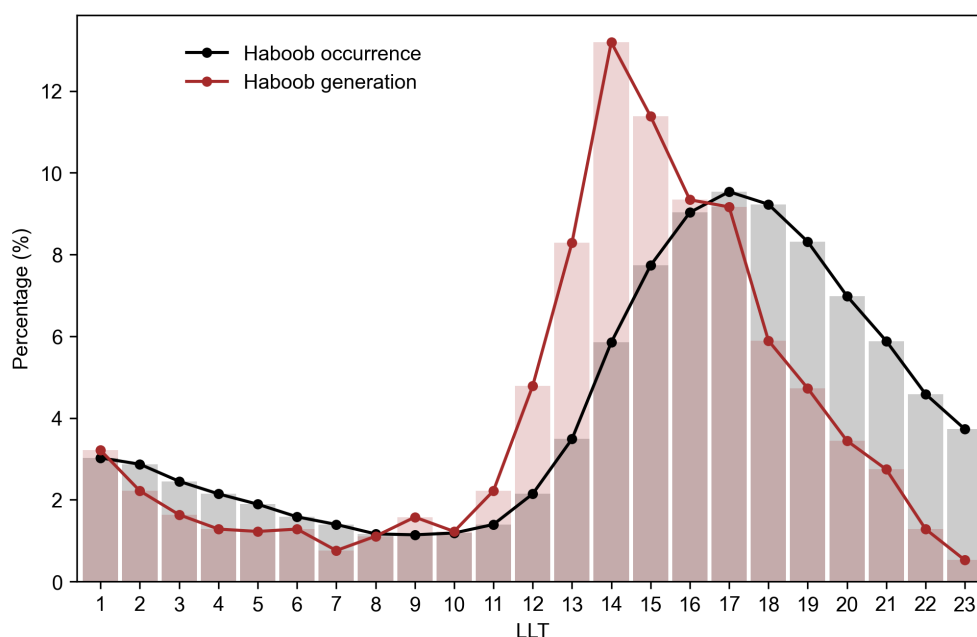


Figure 10. Diurnal cycle of haboob occurrence (black bars and line) and haboob generation (red bars and line), each expressed as a percentage of the daily total. Times are converted from UTC to longitude-based local time (LLT) based on the centroid of identified haboob leading edge points.

23 h (19 h). The maximum lifetimes reported by Allen et al. (2015) are consistent with our results, whereas our median lifetimes falls between the values reported for 2011 and 2012.

As shown in Fig. 11b, the number of haboobs increased steeply with size for small sizes, reached a maximum at 100–125 km, and then declined approximately exponentially. The results of the size analysis confirmed that the haboobs occurring in our simulation were mesoscale events (spatial extent between several kilometers and 1000 km).

Overall, the behavior of haboob size (Fig.11b) appeared similar to that of haboob lifetime (Fig.11a), except for the increase at small sizes. This increase resulted from the removal of short-lived haboobs and disappeared when short-lived haboobs were included (not shown). This might imply that larger haboobs persist longer than small ones. To investigate this possibility, the maximum size and lifetime were calculated together for each haboob. As shown in Fig.11c, a tendency towards larger sizes was visible for longer lifetimes, although these events were less frequent and thus less prominent in the figure. It was also apparent that for a given lifetime, haboobs can assume a wide range of sizes and vice versa. Hence, despite the observed tendency, no clear relationship existed between the lifetime and maximum size of haboobs in our simulation.

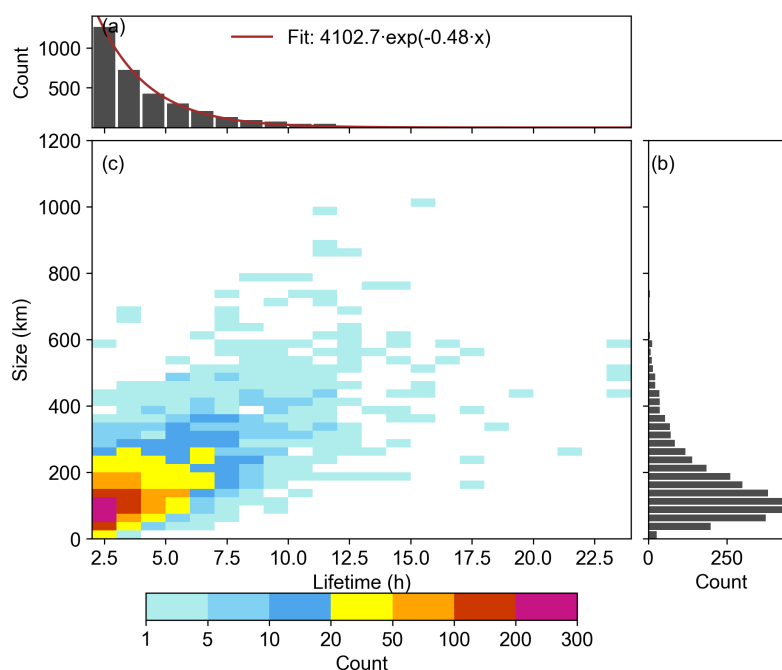


Figure 11. (a) Lifetime histogram for the detected haboobs. Short-lived haboobs (lifetime < 2 h) were filtered out (see Sec. 3.1.4). The red line represents the fitted exponential distribution. (b) Histogram of maximum haboob sizes. (c) Two-dimensional histogram showing the joint distribution of lifetime (x-axis) and maximum haboob size (y-axis). Shading represents the number of haboobs within each bin. Lifetime and size are binned at intervals of 1 hour and 25 km, respectively.

4.4 Dust emission by haboobs

325 The contribution of haboobs to the total dust emission exhibited strong spatial and seasonal variability (Fig. 12). The largest local contributions occurred along the Sahel region, extending from West Africa across Niger and Chad toward Sudan, where haboobs accounted for more than 50% of the total dust emission (Fig. 12a). Despite these large local contributions, the annual domain-mean annual contribution was 6.65% in our simulation, indicating that substantial dust emissions also occurred over broad regions where haboobs contributed only a small fraction of the total dust emission. Similar to haboob occurrence (Fig. 330 8), the haboob contribution also exhibited a pronounced seasonal cycle. In DJF, haboobs accounted for only 0.14% of the total dust emission. During MAM, haboob activity became more prominent and contributions increased over the Sahel and parts of the Arabian Peninsula, with a domain-averaged contribution of 6.25%. The largest contributions (9.72%) occurred during JJA, when haboob activity reached its peak. As in the annual distribution, the Sahel belt showed the largest contribution of haboobs to total dust emission. Besides the primary Sahel hotspot, several secondary localized hotspots were visible over the 335 Atlas region and southern Arabian Peninsula. In SON, the contribution decreased again to 4.05%. These results demonstrate



that although haboobs contribute only modestly to the annual domain-integrated dust emission, they become an important dust-emission mechanism locally and during periods of enhanced convective activity, particularly over the Sahel during JJA.

The spatial pattern of haboob contribution was consistent with that reported by Pantillon et al. (2016), although the absolute contribution in our simulation was smaller. The quantitative difference may arise from several aspects. First, Pantillon et al. (2016) estimated dust uplift potential rather than dust emission fluxes, which may have led to an overestimation of haboob contribution. Second, their results show larger contributions in regions of complex topography, whereas topographic signals were excluded in our analysis. Compared to observational estimates, our estimated haboob contribution also appears to be small. For example, Allen et al. (2013) reported that 45% of the dust observed at Bordj Badji Mokhtar was associated with locally emitting cold pool outflows. However, their estimate was based on nephelometer scattering and small nephelometer scattering events were excluded. In contrast, our estimate was derived from modeled dust emission fluxes and included all emission events.

Finally, several methodological and model related factors may contribute to the relatively small contribution obtained here. First, dust emission fluxes in our model were integrated over hourly intervals, whereas the identified leading edges and cold pool regions were based on instantaneous fields at discrete output times. This temporal mismatch implies that emissions generated during the propagation of a haboob within a given hour may not be fully captured by the cold pool position at the analysis time, potentially leading to an underestimation of haboob contribution. Another possibility relates to the simulated diurnal cycle of dust emission. Figure 13 shows that total accumulated dust emission exhibited a pronounced peak around midday (11–12 UTC) and decreased thereafter, while haboob activity was more pronounced in the afternoon (Fig.10). As a result, the fractional contribution of haboobs remained low during the midday dust emission maximum and increased during the afternoon hours. The mean contribution between 4–12 UTC was only 1.33%, whereas after 12 UTC it increased to 20.14%. This temporal phase difference between the peak in total dust emission and haboob activity reduced the overall contribution attributed to haboobs. While previous studies show a different diurnal structure of dust emission with a stronger afternoon peak (Pantillon et al., 2016; Heinold et al., 2013; Pantillon et al., 2015; Yu et al., 2021), the focus of this study is on the objective identification and characterization of haboobs within a convection-permitting model framework. The influence of the simulated dust emission diurnal cycle on the estimated haboob contribution will be investigated in the future.

5 Case Studies

To illustrate the performance of the proposed detection algorithm under different convective environments, we present two representative haboob events over Mali. The first case represents a relatively compact haboob, while the second is associated with a more organized squall-line-like convective system.

5.1 Case 1: Haboob on 4th June 2011, 14 to 20 UTC

The first case illustrates the performance of the algorithm for a relatively compact haboob undergoing continuous structural evolution. By 15 UTC, a well-developed cold pool had formed, producing a divergent near-surface outflow and a semi-circular

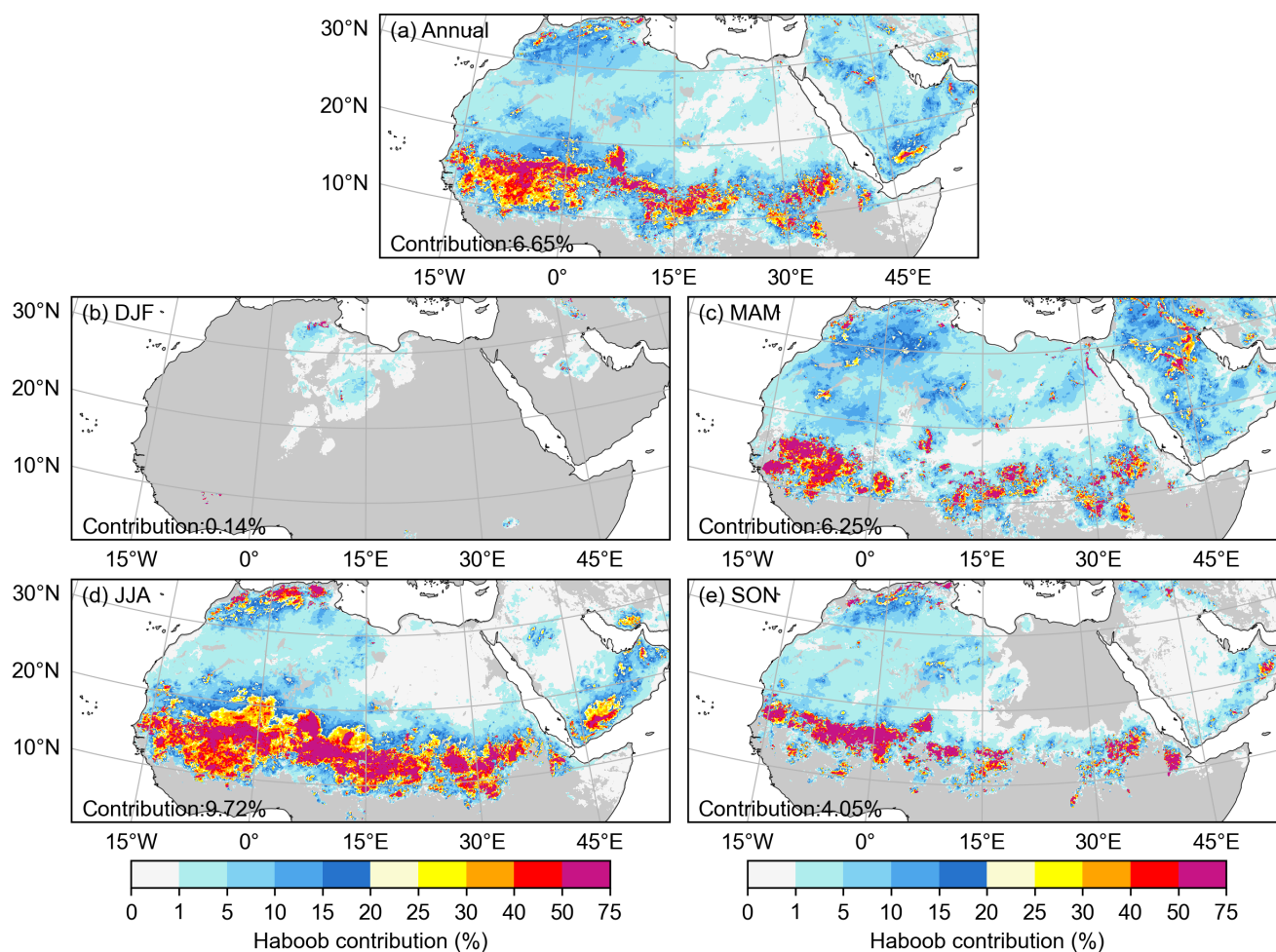


Figure 12. Spatial distribution of the contribution of haboobs to the total dust emission for (a) the whole year, for the seasons (b) DJF, (c) MAM, (d) JJA, and (e) SON. The domain-mean haboob contribution to total dust emission is shown in the lower-left corner of each panel.

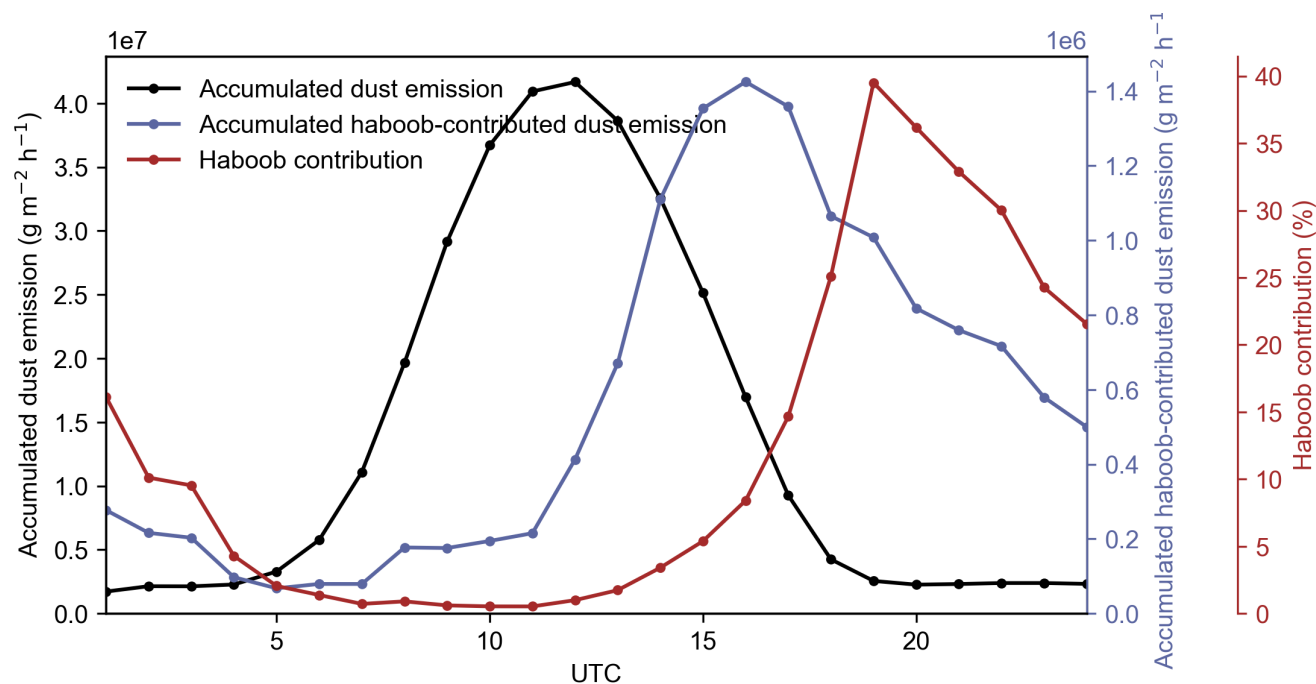


Figure 13. Diurnal cycle of accumulated total dust emission (black line and LHS axis), accumulate haboob-contributed dust emission (blue line and axis), and the fractional contribution of haboobs to the total dust emission (red line and axis). The dust emission values represent hourly integrated emissions from the model, summed at each UTC hour over the full year of 2011 and the spatial domain.

gust front characterized by strong low-level convergence and an arc-shaped updraft at 850 hPa (Figs. 14a–c). The algorithm successfully identified this gust front as the haboob leading edge. Surface dust concentrations were mainly confined to the northern part of the haboob, whereas emissions remained weaker over the southern sector due to the higher vegetation fraction (Fig. 14c).

As the system evolved, a small secondary convective cell developed east of the main storm and subsequently merged with it (Figs. 14d–f). Despite this interaction, both features were consistently assigned to the same haboob by the tracking algorithm, and the corresponding cold pool region correctly encompassed both structures. By 18 UTC, the merged system exhibited two localized outflow centers while maintaining a well-organized arc-shaped leading-edge (Figs. 14g–i). The identified leading edge continued to closely follow the active dust-emitting boundary, demonstrating that the algorithm remains robust despite substantial changes in storm structure during the event lifetime.

5.2 Case 2: Haboob on 5th June 2011, 10 to 22 UTC

The second case illustrates the performance of the algorithm for a more complex squall-line-like convective system. Initially, several scattered convective cells developed over western Mali before gradually organizing into an elongated convective line

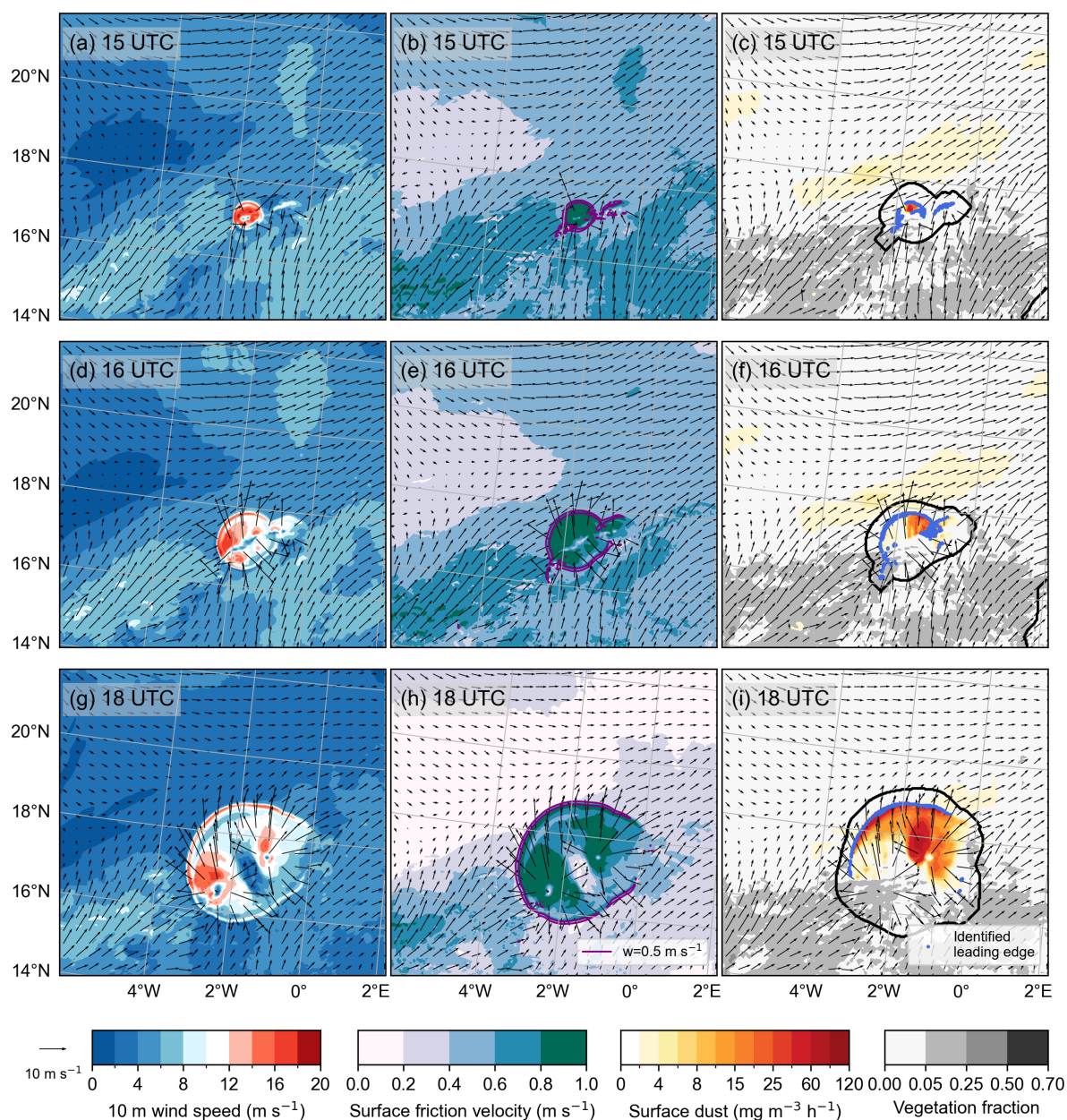


Figure 14. Spatial distributions of (a), (d), (g) 10 m wind speed, (b), (e), (h) surface friction velocity, and (c), (f), (i) surface dust concentration at, respectively, 15, 16, and 18 UTC on 4 June. 10 m wind vectors are shown in each panel. Purple contours in (b), (e), and (h) represent vertical wind velocity at 850 hPa with a value of 0.5 m s^{-1} . Blue dots in (c), (f), and (i) indicate the identified haboob leading edge points. Black contours indicate the identified cold pool regions used to attribute dust emissions to haboobs. Gray shading represents the vegetation fraction.

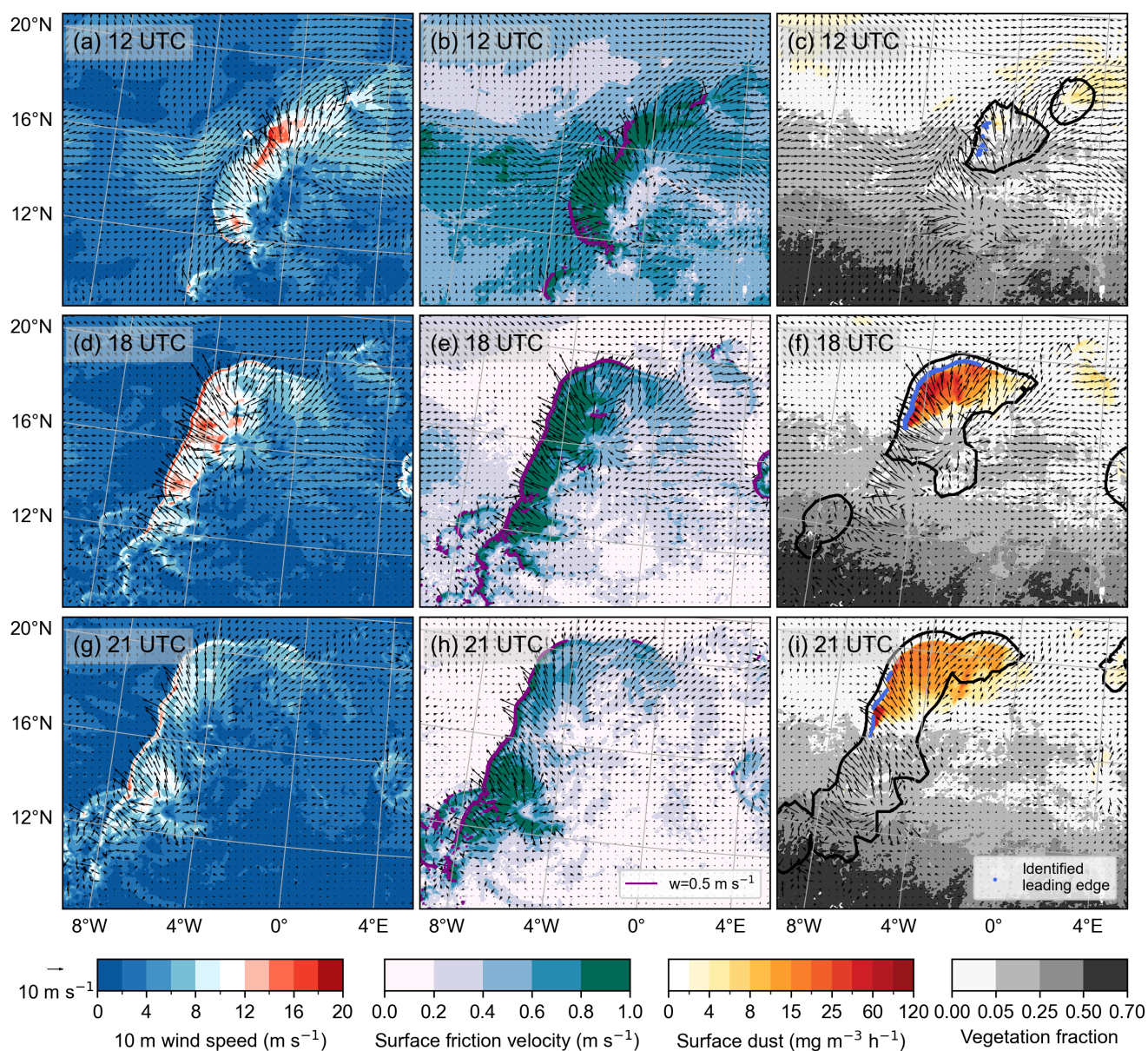


Figure 15. Same as Fig. 14, but for a haboob on 5th June 2011 at (a)–(c) 12 UTC, (d)–(f) 18 UTC, and (g)–(i) 21 UTC, respectively.



(Figs. 15a–b). By 18 UTC, the associated cold pool had extended to approximately 900 km in length, producing a broad outflow with two distinct outflow centers (Figs. 15d–f). Although enhanced 10 m winds and surface friction velocity were present along most of the leading edge, elevated surface dust concentrations occurred mainly along its northern section. Consequently, only this northern portion satisfied the haboob detection criteria and was identified as the haboob leading-edge (Fig. 15f). The presence of two distinct outflow centers caused the watershed algorithm to divide the cold pool into two regions. However, only the northern part was connected to the identified leading edge and was therefore retained for dust-emission attribution (Fig. 15f). As the northern outflow weakened, the detected leading-edge and cold pool region became more spatially coherent and continuous (Figs. 15g–i). It should be noted that, although the detected cold pool region does not always fully encompass the entire dynamical outflow (e.g., at 18 UTC in 15d–f), it successfully captures the portion directly associated with dust uplift and is therefore suitable for dust-emission attribution. Applications focusing specifically on the detailed structure of cold pools may require additional refinement of the detection algorithm.

Together, these two case studies demonstrate the effectiveness of the proposed algorithm across different haboob morphologies and stages of evolution.

6 Conclusions

Mineral dust is an important component of the Earth system with various influences on local and global scales. Haboobs are considered a major contributor to dust uplift over North Africa and the Middle East, yet objective identification and quantification in convection-permitting simulations have remained challenging. In this study, we developed HITRA v1.0, an automated framework for haboob identification, tracking, and dust-emission attribution in convection-permitting simulations. The framework combines objective identification of haboob leading edges, temporal event tracking, cold-pool segmentation, and dust-emission attribution into a reproducible workflow capable of generating both grid-point and event-level haboob catalogues.

HITRA was applied to a one-year convection-permitting MONARCH simulation covering North Africa and the Middle East to evaluate both the performance of the algorithm and the realism of simulated haboobs. The resulting haboob catalogue provides a comprehensive characterization of simulated haboob activity. The identified characteristics—including the concentration of events along the Sahel, a pronounced boreal-summer maximum, afternoon-to-evening occurrence, mesoscale spatial extents, and lifetimes of a few hours—are broadly consistent with evidence from previous observational and modeling studies, which have generally examined only individual aspects of haboob activity. Two representative case studies further demonstrated the ability of the framework to identify haboob leading edges, track events through storm mergers and multiple outflow centers, and delineate the cold-pool regions used for dust-emission attribution.

HITRA also enables a systematic quantification of the contribution of haboobs to dust emissions. In the present simulation, haboobs accounted for 6.65% of the annual domain-total dust emission and 9.72% during JJA, with local contributions exceeding 50% over parts of the Sahel. These estimates are lower than the approximately 20% annual contribution inferred by a previous modeling study (Pantillon et al., 2016). This difference likely reflects methodological differences, including the use of



interactively modeled dust-emission fluxes in our study rather than dust-uplift potential, and the exclusion of topographically induced signals.

415 While applying and testing HITRA with additional models, time periods and climatic regions will be valuable, the results presented here demonstrate that HITRA provides an automated framework for investigating haboobs and their role in the dust cycle. Unlike observational approaches, this modeling framework allows continuous spatial and temporal tracking of haboob evolution and associated dust emission. The methodology presented here therefore opens new opportunities for objective intercomparison of haboob climatologies across models, application to other dust-prone regions, investigation of the processes
420 controlling haboob activity, and assessment of their contribution to the mineral dust cycle under present and future climates.

Code and data availability. The source code of HITRA v1.0, developed in Python 3.10, is archived on Zenodo at

<https://doi.org/10.5281/zenodo.21900922> (Unser et al., 2026). The archive includes the code for haboob leading-edge identification and tracking, cold-pool identification, and haboob dust-emission attribution. It also contains the post-processing code used to derive event-level diagnostics, including initiation time, lifetime, and maximum size. The MONARCH model output used as input to HITRA, together with the
425 corresponding HITRA output, is available at <https://doi.org/10.35097/009hk9t0hr9by9r0> (Li et al., 2026).

Author contributions. TU developed the initial version of the haboob-tracking algorithm and drafted the manuscript. RL revised and further-developed the haboob-tracking algorithm, created most figures, and contributed to the manuscript text. MK conducted the MONARCH simulation, supervised the work, and revised the entire manuscript. PK and CP co-supervised the work. FB contributed to data handling. MC and OJ supported execution of the MONARCH run. All authors contributed to revising the manuscript.

430 *Competing interests.* The authors declare that they have no competing interests.

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