Modeling of mineral dust emissions with a Weibull wind speed distribution including subgrid scale orography variance

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ABSTRACT

The modeling of mineral dust emissions requires a fine knowledge of the wind speed close to the surface. In regional and global models, Weibull distributions are often used to better represent the subgrid scale variability of the wind speed. This distribution mainly depends on a $k$ parameter, itself currently parameterized as a function of the wind speed value. In this study, we propose to add the potential impact of the orography variance in the wind speed distribution by changing the $k$ parameter value. Academic test cases are designed to estimate the parameters of the scheme. A realistic test case is performed over a large domain encompassing the northern part of Africa and Europe and for the period of 1st January to 1st May 2012. The simulations’s results are compared to PM$_{10}$ surface concentrations and AERONET Aerosol Optical Depth and Aerosol Size Distribution. We show that with the orography variance, the simulations results are close to the ones without, showing this additional variability is not the main driver of possible errors in mineral dust modeling.

1. Introduction

For many geophysical studies, the wind speed close to the surface is a key parameter. This includes the analysis and modeling of mineral dust emissions. Primarily, the understanding of these emissions was performed using in situ or wind tunnel experiments, (Gillette and Passi 1988; Shao et al. 1993). This means that the deduced parameterizations were first mainly representative of a local spatial area. Using these experimental studies, Dust Production Models (DPM) were designed and later implemented in regional and global transport models. The transition between the local scale and the large scale modeled fluxes is ensured by using tuning parameters. For example, Tegen and Fung (1994) uses a simple relationship for the vertical flux estimation, including a scaling factor, Marti corena et al. (1997) linked the horizontal $F_h$ (saltation) to the vertical $F_v$ (sandblasting) flux using constant $\alpha$ factors as $\alpha = F_v/F_h$ (with a dependency on the soil characteristics only). Other well-known and used DPMs such as Alfaro and Gomes (2001), Shao (2001) or Kok et al. (2012), among others, are more realistic and calculate the vertical dust flux using more parameters. But even if they are more complex, they are also using tuning factors. Once the DPM scheme is included in transport models, simulations are most often validated with derived budget but not direct measurements of emissions (as this is not possible to measure emissions out of a wind tunnel). The most employed proxy is the Aerosol Optical depth (AOD) derived from satellite data or photometers from the AERONET network, (Holben et al. 2001). More recently, other derived parameters are used such as SEVIRI to estimate the hourly frequency of emissions, (Schepanski et al. 2007). These AOD measurements are the results of vertically integrated concentrations, converted using uncertain optical properties of aerosols. It is therefore difficult to directly use these data to better understand or constrain the surface emissions process. This explains that the DPM may vary a lot between models, leading to a large variability of the mineral dust emissions estimates, (Huneeus et al. 2011; Cuevas et al. 2015).

To fill the gap between locally estimated emissions and a regional scale model, recent studies explored the way to describe the DPM’s input parameters with distributions in place of single mean values (Grini and Zender 2004; Pryor et al. 2005; Menut 2008). This corresponds to the way to represent variables also with their subgrid scale variability. This variability may be taken into account for many parameters in the DPM: recently, Menut et al. (2013b) use spatially high resolution databases of roughness lengths, soil and surface parameters to represent the existing variability in a model grid cell representing several tens of squared kilometers.
This is also essential for the wind speed used in the emissions calculation. The mean wind speed used in a model often represents averaged values both in the temporal and spatial dimensions. But, as the mineral dust emissions in a threshold problem, the use of a single mean value may induce large modeling errors. For example, for particular soil conditions, emissions of dust may appear only up to 8.5 m s$^{-1}$; if the "real" mean wind speed is 8 m s$^{-1}$, there is no emission at all. But if the "modeled" wind speed is 9 m s$^{-1}$, emissions are calculated. This model error is possible since the wind speed model uncertainty is $\approx 1$ m s$^{-1}$ in regional models (see Gómez-Navarro et al. 2015) among others. To avoid these possible large errors due to the conjunction of wind speed uncertainty and threshold calculation using this wind speed, DPM use wind speed distributions such as the Weibull distribution, (Weibull 1951). These distributions represent the fact that the mean wind speed may be biased or uncertain, but is also a way to represent the fact that during one hour and for a large grid cell, the instantaneous wind speed may vary a lot.

In this study, the main goal is to improve the subgrid scale variability of the mean wind speed by adding additional information in the $k$ parameter estimation. This additional information is the orography variance of a model grid cell. The choice to add this specific variability was done because this information is available but not used in the model and because it seems logical that the surface wind speed is not spatially constant over surfaces of tens of squared kilometers. Then, in a model, when using a "mean" wind speed, it is clear that this value does not reflect completely all possible values observed in a grid cell where the orography may vary.

By adding a relationship between $k$ and the orography, we add realism to the simulation and we also expect to reduce the uncertainty linked to the model resolution (the more realistic subgrid scale variability is taken into account the less the results depend on the horizontal resolution). Using the WRF and CHIMERE models, simulations are done with and without the modification of $k$. Using comparisons to measurements, we quantify if the modeled results are improved.

First, the data and tools used in this study are presented with the observations in Section 2 and the models in Section 3. The Weibull distribution is presented in Section 4 and the proposed modified formulation of the shape parameter $k$ in Section 5. Results with an academic test case are presented in Section 6. Then, in Section 7, the impact of this additional term is evaluated on a realistic test case representing the simulation of the period January-April 2012 over a large domain encompassing the northern Africa (including Sahara and Sahel) and the Mediterranean region. Conclusions are presented in Section 8.

2. The observations

In this study, an academic and a real test case are presented. For the real test case, several observations are used: (i) the surface concentrations of PM$_{10}$ as measured by the Sahelian Dust transect (SDT), (ii) the AERONET photometers measurements for the Aerosol Optical Depth (AOD), the Angstrom exponent (Ae) and the Aerosol Size Distribution (ASD). Finally, the statistical scores used to quantify the results are presented in this section.

a. Surface concentrations of PM$_{10}$

For the surface concentrations of PM$_{10}$, we use the Sahelian Dust Transect (SDT) measurements. These measurements are performed in Banizoumbou (Niger), Cinzana (Mali), M'Bour and Bambe (Senegal) as described in (Martiorena et al. 2010). The concentrations are measured using a Tapered Element Oscillating Microbalance with a PM$_{10}$ inlet. These microbalances are at the same place that the photometers of the AERONET network.

b. Aerosol Optical Depth

The stations are selected to be representative of different locations, then different proximities to mineral dust sources. Banizoumbou and Cinzana are located in the center of western Africa and also correspond to stations of the SDT. They are considered as locations close to the sources. Dakar is located close to the coast in the western side of west Africa and Izana (Tenerife Island) is located in the Canary Islands. Dakar and Izana are more representative of stations "under mineral dust plumes" after long-range transport.

The aerosol optical properties are compared between observations and model using the AERONET (AErosol RObotic NETwork) measurements (Holben et al. 2001). First, the comparison is done using the Aerosol Optical Depth (AOD) and for a wavelength of $\lambda=550$nm. Second, the comparison is performed using the Aerosol Size Distribution (ASD) estimated after inversion of the photometers data as described in (Dubovik and King 2000). The level 2 data are used. For each AERONET station used in this study and listed in Table 1, the inversion algorithm provides volume particle size distribution for 15 bins, logarithmically distributed for radius between 0.05 to 15 $\mu$m.

c. Statistical scores

The statistics are calculated for correlation (R$_{s}$), Root Mean Square Error (RMSE) and bias. The correlation used in this study is the Pearson’s correlation. Each correlation provides specific information on the quality of the simulation. The temporal correlation, noted R$_{c}$, is estimated station by station and using daily averaged data in order to have homogeneous comparisons between all variables. This correlation is directly related to the variability
Thus:

\[
\text{Root Mean Square Error is expressed as:}
\]

\[
\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^{T} \sum_{i=1}^{I} \left( \frac{O_{t,i} - M_{t,i}}{O_{t,i}} \right)^2}
\]  

for all stations \( i \) and all times \( t \).

### 3. The models

For the results calculations, several models are used. First, we describe the Dust Production Model. Second, and for the real test case, we describe the Weather and Research Forecasting (WRF) model which calculates the meteorological fields and the CHIMERE chemistry-transport model which calculates the concentrations of mineral dust in the troposphere.

#### a. The Dust Production Model

The mineral dust flux is estimated following two steps. First, the saltation flux is calculated with the scheme of White (1986):

\[
F_s(D_p) = \frac{\rho_{air}}{g} \left( 1 - \frac{u_s^T}{u_*} \right) \left( 1 + \frac{u_s^T}{u_*} \right)^2
\]  

where \( u_s \) is the "saltation" friction velocity, i.e., the friction velocity calculated using the roughness length, \( z_0 \). The roughness length is estimated using the global 6 km horizontal resolution 'Global Aeolian Roughness Lengths from ASCAT and PARASOL' dataset, Prigent et al. (2012). \( g \) is the acceleration of gravity, \( g = 9.81 \text{ms}^{-2} \), \( \rho_{air} \) is the air density (depending on the meteorological model).

\( u_s^T \) is the threshold friction velocity depending on the soil particle diameter size \( D_p \) and \( z_0 \) and is calculated following the parameterization of Shao and Lu (2000):

\[
u_s^T(D_p) = \sqrt{a_n \left( \frac{\rho_p g D_p}{\rho_{air}} + \frac{\gamma}{\rho_{air} D_p} \right)}
\]  

with the constant parameters \( a_n = 0.0123 \) and \( \gamma=300 \text{kg.m}^{-2} \). The particle density, \( \rho_p=2.65 \text{10}^3 \text{kg.m}^{-3} \) is chosen to be representative of quartz grains clay minerals. The saltation flux is estimated only when \( u_s > u_s^T(D_p) \) for a given soil particle diameter \( D_p \). One saltation flux is calculated for each grain size of the soil distribution, then all fluxes are integrated.

Second, the sandblasting flux is calculated following the Alfaro and Gomes (2001) scheme, modified in Menut et al. (2005). The calculation is based on the partitioning between the dust cohesion energy and the kinetic energy of each saltating aggregate. The emitted mineral dust is split into three aerosols modes (fine, coarse, and big). These modes are represented using log-normal distributions with diameters \( d_1=1.5 \text{10}^{-6} \text{m} \), \( d_2=6.7 \text{10}^{-6} \text{m} \) and \( d_3=14.2 \text{10}^{-6} \text{m} \) and their associated standard deviation, respectively \( \sigma_1=1.7 \), \( \sigma_2=1.6 \) and \( \sigma_3=1.5 \). For each mode, a kinetic energy is defined and the flux is calculated as:

\[
F_{vm,i}(D_p) = \sum_{k=1}^{N_{class}} \frac{\pi}{6} \rho_p \beta p_i(D_{p,k}) d_{m,i}^3 dF_h(D_{p,k})
\]

where \( N_{class} \) is the number of intervals discretizing the soil size distribution in the range \([D_{p,\text{min}} : D_{p,\text{max}}]\) and \( d_{m,i} \) the mean mass diameter. \( \beta \) is a constant as \( \beta=16300 \) and \( p_i \) are factors depending on the soil size, after Alfaro and Gomes (2001). One specificity of this scheme is that,
addition to the mean flux value, the emission size distribution depends on the wind speed. The higher the wind speed, the finer the emitted particles.

The surface and soil databases are described in Menut et al. (2013b). The soil characteristics are from the STATSGO-FAO database, (Nachtergaele et al. 2009), a global dataset with a native resolution of $30' \times 30'$. For the surface characteristics, the NCAR USGS database is used, with the same resolution than the soil database, (Loveland et al. 2000). For each model grid cell, we thus have the relative percentage of all soil and surface characteristics. For each of these percentage, a sandblasting flux is calculated then cumulated to have the total sandblasting flux in each model grid cell.

Complementary to the soil and surface characteristics, an erodibility factor is also necessary to estimate the relative part of the grid cell which could emit mineral dust. A global database was derived using MODIS satellite data to estimate this factor, as described in Beegum et al. (2016). A map of erodibility is presented in Figure 1.

This Figure also shows the orography variance (in m$^2$) provided by the WRF model database. This variance varies between 0 to 15000 m$^2$ on the domain. The most important variability is observed over mountainous areas, when the resolved topography corresponds to an average of very different altitudes above sea level.

b. The WRF and CHIMERE model

The WRF and CHIMERE models are used to calculate the concentrations of aerosol in the troposphere. The system is an ‘off-line’ coupling model meaning that the meteorological fields are first calculated with WRF, then these meteorological fields are used by CHIMERE for the transport.

WRF is used in its 3.6.1 version, (Skamarock et al. 2007). This regional modeling uses NCEP global meteorological fields using a spectral nudging to ensure that the large-scale circulation is well taken into account. The complete set-up for this model is presented in (Menut et al. 2016).

CHIMERE is used in its version described in Menut et al. (2013a) and including the last updates presented in Mailler et al. (2017). For this study, the gaseous and aerosol chemistry is not used. The only aerosol taken into account is mineral dust: emissions, transport, mixing and wet and dry deposition. For all other parameters, we also used exactly the same configuration as in (Menut et al. 2016). The modeled AOD is calculated by FastJX for several wavelengths, (Wild et al. 2000). The boundary conditions for mineral dust are those of the climatology provided by GOCART, (Ginoux et al. 2001) and described in (Menut et al. 2013a).

In order to quantify the impact of our changes during a long period, the simulations ranges from 1st January to 1st May 2012. These four months correspond to the dry period in western Africa, when major mineral dust events occur. The modeled domain has an horizontal resolution of $60 \times 60$km and represents a large domain encompassing the northern part of Africa and the Mediterranean sea, as presented in Figure 1. This domain is strictly the same for the WRF and the CHIMERE models. The horizontal resolution was selected for different reasons: (i) this study is about subgrid scale variability: with this resolution of tens of squared kilometers, the variability is non negligible, (ii) for mineral dust studies, it is important to have a large modelled domain, encompassing all possible sources and long-range transport. This simulations ranging 4 months and over a large domain, this resolution make the computational cost manageable. Note that this resolution was used in previous studies, such as Menut et al. (2016), Briant et al. (2017), Menut et al. (2017) and shows satisfactorily results compared to observations.

The main goal of this study is to change the wind speed. This wind speed is calculated by WRF and then used by CHIMERE for several processes: the transport, the calculation of the friction velocity (for the dry deposition) and the mineral dust emissions. The use of the Weibull distribution is made only in CHIMERE and only for the mineral dust emissions. For all other processes, the mean wind speed remains unchanged and as it is provided by WRF.
4. The Weibull distribution

This section presents the main concept of the Weibull distribution, the parameters to define and the way to estimate them.

a. The Weibull distribution formulation

The Weibull distribution is expressed as the following probability density function, following (Babiker et al. 1987):

\[
p(U_{sg}) = \frac{k}{\lambda} \left( \frac{|U_{sg}|}{\lambda} \right)^{k-1} \exp \left[ - \left( \frac{|U_{sg}|}{\lambda} \right)^k \right]
\]  

(8)

where \(|U_{sg}|\) is the subgrid-scale wind speed value, \(p(U_{sg})\) is its probability density function, \(k\) is a dimensionless shape parameter and \(\lambda\) (m s\(^{-1}\)) is a scale parameter related to the mean of the distribution (in general the mean wind speed value, \(|U|\)).

The subgrid-scale wind speed \(|U_{sg}|\) is estimated from the grid-scale mean wind speed \(|U|\) as:

\[
|U_{sg}| = \frac{2i}{N_w} |U|
\]  

(9)

where \(i\) ranges from 1 to \(N_w\), the number of subgrid-scale wind speed values defined to estimate accurately the distribution.

The \(k\) value is estimated with the \(k\) parameter, which enables to reduce the Weibull distribution uncertainty to the \(k\) parameter only. The expression of \(\lambda\) is:

\[
\lambda = \frac{\overline{U}}{\Gamma \left( 1 + \frac{1}{k} \right)}
\]  

(10)

with \(\Gamma\) the gamma function. The main problem for an accurate calculation of the Weibull distribution is thus focused on the accuracy of the \(k\) parameter.

b. Current estimate of \(k\)

The sensitivity to \(k\) is a well-known problem. Numerous studies were dedicated to its study and we present here only a few examples. Using measurements made at one site, Babiker et al. (1987) made a sensitivity study to quantify the impact of the mineral dust emissions fluxes to several \(k\) values ranging from 1 to 3. Also using measurements (30 years and 1432 different measurements sites in US), Gillette and Passi (1988) estimated \(k\) values between 0.5 and 3.86. Christofferson and Gillette (1987) proposed a methodology to estimate the \(k\) value from numerous wind speed observations. (Pérez et al. 2007) used sodar data to retrieve wind speed values close to the surface: in this case, several \(k\) values are tested and compared to the observations, in a range from 1 to 4. Kelly et al. (2014) studied the potential variability of \(k\) and presented results with values ranging between 1.5 and 3. Gryning et al. (2015) presented a similar technique, but using mast and lidar measurements and concluded that \(k\) varies between 1.8 and 3.1 (depending on the altitude and the sites localization). (He et al. 2010) used wind data from 720 stations (from 1979 to 1999) and showed that the \(k\) parameter could depend on the atmospheric stability: the Weibull distribution is narrower during the night, due to intermittent turbulence. Statistically, they showed that the \(k\) value could depend on the wind speed value with a larger distribution for weak winds (high wind variability) and narrower for strong winds (well established wind speed regimes). The first studies showed that a constant value of \(k\) is not realistic and this parameter has to be variable in space and time.

More specifically for the mineral dust emissions problem, some other studies were already dedicated to the best as possible estimate of \(k\). Menut (2008) used a constant value of \(k\), limiting the variability. It was done to ensure a certain stability of the calculation in case of operational forecast calculations (i.e no day to day tuning of the model). This approach has to be replaced in models in order to be more realistic. (Ridley et al. 2013) made two simulations for the same domain and the same period: one with a high resolution to explicitly calculate the wind speed variability. The second one, with a coarsest resolution, to test the deduced \(k\) parameters used with a Weibull distribution. The approach is realistic but valid mainly for one studied case. A change in the period of the domain requires to replay the two simulations, fine and coarse.

A relationship between \(k\), the mean wind speed \(|U|\) and its variance \(\sigma_U\) was presented by Justus et al. (1978) (hereafter called J78). This scheme is the only we found to express the \(k\) value as a function of a meteorological parameter. This is why it was selected for this study. It is expressed as:

\[
k = \left( \frac{\overline{U}}{\sigma_U} \right)^{1.086}
\]  

(11)

A direct relationship linking \(k\) and \(\sigma_U\) is used in (Grini and Zender 2004) as:

\[
k = 0.94\sqrt{\overline{U}}
\]  

(12)

This expression does not take into account subgrid scale variability such as the orography. It considers that the Weibull shape mainly depends on the wind speed magnitude. This latter relation is used in many studies such as Su and Toon (2009) with the CAM3 model applied over China, (Zhang et al. 2016) with CAM5 and at the global scale (2° resolution) and Tegen et al. (2006) for the comparison to observed wind values in Bodele. Note that in these studies, they are using a dust production model for
which the size distribution is not dependent on the wind speed (unlike the model used in this study).

An example of wind speed distribution using $k$ constant values ($k=3$ and 4) and the expression of J78 is presented in Figure 2. The distributions are calculated for mean wind speed values of $|U|=8$ and $14$ m s$^{-1}$. These values are just examples of several possible modeled wind speed values.

- For $|U|=8$ m s$^{-1}$, the distribution ranges from 0 to 15 m s$^{-1}$. The J78 shape parameter value is $k=2.66$.
- For $|U|=14$ m s$^{-1}$, the distribution ranges from 0 to 28 m s$^{-1}$. The J78 shape parameter value is $k=3.52$.

Having a $k$ value evolving with the mean wind speed value, it is interesting to notice that, for $|U|=8$ m s$^{-1}$, the J78 distribution has the largest width, when for $|U|=14$ m s$^{-1}$, the distribution has values between the distributions calculated with $k=3$ and 4.

5. Adding the orography variability in $k$

a. The $f_k$ factor

The main goal of this study is to estimate a $k$ value taken into account the orography subgrid variability. This quantity represents a factor directly affecting the surface wind speed and is currently not taken into account in the models using this wind speed. For that, we thus propose to add a variability term to the parameterization of J78. The new $k$ depending on the orography is thus expressed as:

$$k = f_k \left( \frac{U}{\sigma_U} \right)^{1.086}$$  \hspace{1cm} (13)

where $f_k$ is a factor, using a simple function, respecting the following rules:

- First, we have to ensure that $k$ will evolve around its mean value and within an acceptable range. We thus define two constants, $f_{k,\text{min}}$ and $f_{k,\text{max}}$, designed to act as limiters. They represent the minimum and maximum possible factor around the mean $k$ value.
- We consider that over flat terrain, the wind speed module would have a lower variability that over complex terrain with a changing orography. The value of $f_k=1$ represents a ”mean” orography variance in the selected range of possible values of orography. For $f_k < 1$, we have $k$ decreasing, representing a more peakly wind speed distribution and thus an orography variance less important than the “mean” value: over flat terrains, the wind speed is more spatially homogeneous, because there is no orography.
- The change is designed to act only over erodible surfaces since this is only applied for mineral dust emissions. It is thus necessary to find the maximum of orography variance until where the mineral dust emissions occur. The orography variance may be very large over mountainous areas but these areas are non erodible (being mainly constituted of rocks) and are thus not taken into account.
- We also want to have a non linear dependency between $k$ and the orography variance in order to have a smooth change between the minimum and maximum orography variance values.

![Fig. 3. The $f_k$ factor variability as a function of the orography variance.](image-url)
\[ f_k = f_{k,\text{min}} + (f_{k,\text{max}} - f_{k,\text{min}}) \times \left( 1 - \frac{c}{1 + a \exp \left( -b \frac{\sigma_z}{\sigma_{z,\text{max}}} \right)} \right) \]  

(14)

where: \( \sigma_z \) is the orography variance of the model cell where the dust flux is calculated. \( \sigma_{z,\text{max}} \) represents the maximum of orography variance for which we want to reduce the \( k \) value. The \( a, b \) and \( c \) values are just constants dedicated to modify the shape of the function. Here, we want to have a smooth function and we selected \( a=20, b=10, c=1 \). Some sensitivity tests were done and results were not sensitive to a change in these values. A schematic representation of \( f_k \) is presented in Figure 3. For this study, we selected a \( f_k \) decrease/increase of \( \pm 20\% \), leading to define \( f_{k,\text{min}}=0.8 \) and \( f_{k,\text{max}}=1.2 \). These values were arbitrarily selected but represent "reasonable" variability of the \( k \) parameter, regarding the numerous studies having fitted this parameter using wind speed measurements.

6. Academic test case modeling

In order to understand the variability of \( k \) as a function of the mean wind speed and various values of orography variances, a simple academic test case is performed. For this test case, the DPM of Alfaro and Gomes (2001) is used alone, in a 0D context (meaning that there is no time or space, but only a calculation using a varying academic wind speed value). In order to quantify the maximum of the impact of the \( f_k \) factor, the Weibull distribution is calculated with three different hypotheses and results are displayed in Figure 4:

- \( f_k =1 \) corresponding to the J78 scheme without any change
- \( f_k \) with \( \sigma_z=0.01 \times \sigma_{z,\text{max}} \) corresponding to a low orography variability. In this case, we consider that the orography variance corresponds to 1% of the maximum orography variance.
- \( f_k \) with \( \sigma_z=\sigma_{z,\text{max}} \) corresponding to a maximum of orography variability (100%)

Results are first presented in Figure 4 (top) for the evolution of \( k \) depending on the mean wind speed value \( |U| \). For \( f_k =1 \), noted [J78], the \( k \) value regularly increases when \( |U| \) increases. For the two other cases, the increase has a similar trend, but the absolute values of \( k \) differ. For example, and for \( |U|=10 \text{ m s}^{-1} \), we have \( k=3 \) for the J78 scheme, but \( k \approx 3.5 \) and 2.5 when the orography is low and high, respectively (Sigma=1% and Sigma=100%).

For the same three expressions of \( k \), results are presented as Weibull distribution in Figure 4 (middle). The distribution with J78 without any change is in between the two others distributions when \( f_k \) is applied.

Finally, the impact on emissions fluxes are presented in Figure 4 (bottom). The aerosol size fluxes of the emissions flux is presented for \( U_{100}=10 \text{ m s}^{-1} \). The corre-
TABLE 2. Value of the vertical mineral dust flux calculated with the Alfaro and Gomes (2001) scheme and for $U_{10m}$=10 m s$^{-1}$. The vertical emissions fluxes, $F_v$, is in kg m$^{-1}$ day$^{-1}$.

<table>
<thead>
<tr>
<th>Model</th>
<th>$k$</th>
<th>$F_v$</th>
<th>AOD</th>
</tr>
</thead>
<tbody>
<tr>
<td>J78</td>
<td>2.97</td>
<td>53.91</td>
<td>0.92</td>
</tr>
<tr>
<td>J78+Sigma=1%</td>
<td>4.35</td>
<td>39.19</td>
<td>0.54</td>
</tr>
<tr>
<td>J78+Sigma=100%</td>
<td>2.38</td>
<td>60.16</td>
<td>1.10</td>
</tr>
</tbody>
</table>

Emissions are diagnosed for three main modes as defined previously. Here, they are expressed in radius, to be later compared with AERONET measurements. The highest impact on the fluxes appear for the fine mode of the distribution, $r_p=0.75$ µm. This mode corresponds to the optically efficient part of the size distribution. The change of $k$ has thus an impact on the vertical flux but also on the deduced Aerosol Optical depth (AOD). As presented in Table 2, with no variability, AOD=0.92. If the orography variability is taken into account, AOD=0.54 and 1.10 for an orography variance of 1 and 100%, respectively. This huge impact, both on emissions fluxes and on AOD, shows the high sensitivity of the determination of the $k$ parameter for mineral dust model studies.

7. Real test case

The two simulations, without and with the orography impact on the $k$ parameter value, are called hereafter "J78" and "J78+Var_oro", respectively. The simulations containing only mineral dust as aerosol, the results are compared to measurements performed in locations where mineral dust dominates the aerosol composition: the AERONET stations located in Western Africa and the surface PM$_{10}$ measurements of the Sahelian Transect.

a. Determination of the $k$ parameter over the domain

The first step for the real test case is to calculate the parameters involved in equation 14. Among all parameters, it is necessary to select a correct value for $\sigma_{z,\text{max}}$. To do this, we calculate the distribution of the SSO variance. This is calculated for the whole domain and for the erodible surfaces only. The result is displayed in Figure 5. The SSO variability between 0 and 500 m$^2$ represents occurrence between 80 and 90%. Between 500 and 1000 m$^2$, it reduces to less than 10% for both cases. There is more low variability for the whole domain, probably due to the fact that ocean model cells are taken into account. The values higher than 1000 m$^2$ represent a few percents of the distribution. As we want to act mainly on the range where the variability is the most frequent over the erodible areas, we select $\sigma_{z,\text{max}}=1000$ m$^2$.

The results of the $k$ parameter calculation using these criteria is presented in Figure 6. Values are estimated for cells with an erodibility of 10% at least. The frames indicate the main mineral dust sources in Africa. The surface stations are indicated with their names.

The results of the $k$ parameter calculation using these criteria is presented in Figure 6. Values are estimated for cells with an erodibility of 10% at least. The frames indicate the main mineral dust sources in Africa. The surface stations are indicated with their names.
values are defined where the orography is low and these areas represents the majority of the erodible cells for the studied domain.

Globally, we probably will have mineral dust emissions less important than using only the J78 parameterization. But, we expect to have a different spatial variability of the emissions since the change in the \( k \) parameter depends on varying orography over the whole domain.

b. Results for surface concentrations of PM\(_{10}\)

The PM\(_{10}\) surface concentrations are compared between the model and the observations and with an hourly time-step. Results are first presented as time series in Figure 7 and for the sites of Banizoumbou, Cinzana and Dakar. The observations, represented as symbols, shows a large time variability and values are ranging from 0 to 2000 \( \mu g \) m\(^{-3}\).

The results mainly show the high temporal variability of the measurements and the fact that the model is able to reproduce this variability. The "J78+Var_oro" configuration provides PM\(_{10}\) lower that the "J78". This means that over the erodible regions leading to mineral dust measured at these sites, we have an orography variance less important than the mean average value and thus a increased \( k \) parameter, leading to a more peakly Weibull distribution and thus less mineral dust emissions.

The results are quantified as statistical scores in Table 3. The first part of this Table corresponds to the model results for "J78" and the second part to "J78+Var_oro". For the correlation and the RMSE, the best statistical scores are bolded. For the correlation and the RMSE, the results are better for "J78+Var_oro" than for "J78" (except for the correlation in Banizoumbou, but the difference is low and only 0.01). The most important benefit with the "J78+Var_oro" configuration is for the RMSE. This is mainly because the shape parameter \( k \) is increased, leading to a sharper Weibull distribution and thus less variability in the mineral dust emissions. The model error is reduced by at least \( \approx 50\% \) for each of the three stations. This benefit being true for the three stations, and these three stations being not close but representative of different regions, we can expect that this "J78+Var_oro" configuration improves the results in a realistic way.

c. Aerosol Optical Depth time series

Results for the AOD comparisons with the AERONET data and the CHIMERE model outputs are displayed in Figure 8 as time series, from the 1st January to 30 April 2012.

The time series show that several high peaks of mineral dust occurred during the four studied months. For all these peaks, the model is able to retrieve correctly their timing (the correct day and the duration) and their magnitude. A few peaks are missing (as in January in Banizoumbou or mid-April in Izana) but they are very peaked and probably correspond to local events, difficult to catch with the used model resolution, such as convective cold pools or sporadic wind speed extremes. In general, the model is able to estimate the background values and the major dust events. As for the PM\(_{10}\) time series, the "J78+Var_oro" configuration simulates less AOD than the "J78" one.

In order to quantify these results of AOD, statistical values are presented in Table 4. The simulation with the orography variance improves the model results compared to the observations: the RMSE is better for all stations, showing that the model error is globally reduced. For the correlation, the differences between the two simulations.
d. Aerosol Optical Depth maps

As a complement of the time series and the statistical scores, maps of AOD values is presented in Figure 9. The modeled period lasted four months and the maps represent four days during the period: 15th of January, February, March and April 2012 at 12:00 UTC. Note that other maps were analyzed and the discussion and conclusion are similar. The left column represents the AOD absolute values calculated with the "J78+Var_oro" simulation and the right column corresponds to the difference of AOD calculated with AOD(J78+Var_oro)-AOD(J78). The AOD highest values are located in different places according to the day. But for the four days, the "J78+Var_oro" corresponds always to a decrease in AOD, the largest differences being colocated with the highest AOD values. It shows that the use of the orography variance leads to an increase of $k$ and thus a decrease of emissions, thus AOD. It means that the change is mainly applied over erodible areas where the orography variance is low.

For example and for the 15 April 2012, two main plumes are visible: a first one in the center of Africa (over Niger and Chad), and a second one in Guinea and Senegal and transported towards the Atlantic sea. In these plumes, the AOD values reach 2 at the maximum when the 'background values' over Africa are between 0 and 1. For the AOD 'background' values, the differences reach 0.2. In
the plumes, where the AOD are maximum, the differences reach 0.8, corresponding to an important change in the AOD estimation.

e. Aerosol Size distribution

As presented in Figure 4, a change of the k parameter acts on the mineral dust emissions flux magnitude but also on its size distribution. In order to quantify the impact of the k changes on the size distribution, we compare here the model results to the AERONET inversion. In the AERONET database, note that all AOD measurements are not inverted and we had to find available data. Two comparisons are presented but many other size distributions were analyzed and the conclusions are similar. The results presented correspond to available data close to the results showed in Figure 9, and corresponding to the 15 March and April 2012. Comparisons are presented in Figure 10. Note that, here, the distributions are expressed in radius (to be consistent with the raw data provided by AERONET).

For the four days and the four sites, the most important mode corresponds to the “coarse” mode with \( r_p \approx 3.5 \mu m \). Less important, concentrations are visible for the “fine” mode, \( r_p = 0.8 \mu m \), with the model but not in the observations. The simulation using “J78+Var_oro” is closer to the observations than the “J78” simulation. If the “coarse” mode dominates the mass, the “fine” mode explains the most important differences between the two simulations. And for the calculation of AOD as compared with AERONET (with \( \lambda = 550nm \)), this is the most sensitive part of the size distribution. These figures show that the variability of \( k \) acts on the correct part of the size distribution and proves that the RMSE is highly improved for correct reasons.

8. Conclusions

This study examined the impact of the wind speed Weibull distribution on the calculation of mineral dust emissions. This distribution depends mainly on one parameter, \( k \), parameterized as a function of the mean wind speed. In this study, we consider that for regional models, having a grid cell of tens of kilometers, the subgrid scale orography may also be an important parameter to take into account in the estimation of \( k \) since the orography has a direct impact on the value of the mean wind speed close to the surface.

Using the information of subgrid orography variance, we propose an adjustment of the estimation of the \( k \) parameter. We first test this change with academic cases in order to estimate realistic boundaries to the potential evolution of the \( k \) value. Second, we apply this change in the framework of a realistic modeling: four months, from 1st January to 1st May 2012 and over a large domain, encompassing Western Africa and Europe. The modeled results were compared to surface PM\(_{10}\) concentrations and AERONET Aerosol Optical Depth and aerosol size distribution. Correlation, Root Mean Square Error and bias were also calculated. We showed that for a large part of the comparisons between observation and model results, the correlation is slightly improved (\( \approx +0.01 \)) and the RMSE is greatly improved (\( \approx -30\% \)) both for mass and AOD. Over the studied period, a systematic decrease of AOD and PM\(_{10}\) is modeled with the changed \( k \) shape parameter. It means that, over erodible surfaces, \( k \) was increased. Considering the proposed function, it means we are in the range of ‘low’ variability of orography.

Even if the RMSE is better, the correlation is not really improved. It showed that the subgrid scale variability of orography is not the main driver for the mineral dust emissions. This is surprising because a significant impact was expected: the DPM schemes are very sensitive to the mean wind speed and the mean wind speed is sensitive to the orography close to the surface. The fact to have quantified this impact remains useful even if the impact intensity is lower than expected. For processes such as mineral dust emissions, the sub-grid scale variability remains a way to

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<table>
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<tr>
<th>Site</th>
<th>N (%)</th>
<th>AOD</th>
<th>( R_r )</th>
<th>RMSE</th>
<th>Bias</th>
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<td>0.49</td>
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<tr>
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<td>0.44</td>
<td>0.81</td>
<td>0.44</td>
<td>2.05</td>
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**Table 4.** Scores for the comparisons between observations (AERONET) and model (CHIMERE) for the Aerosol Optical Depth (AOD). Results are presented with N (%) the percentage of hourly mean available measurements for the period from 1st January to 1st May 2012, the mean values over the period (called “Obs” and “Mod”, for the observations and modelled values, respectively), the temporal correlation (\( R_r \)), the Root Mean Squared Error (RMSE) and the bias (model minus observations). Values are bolded for the simulation having the highest correlation or the lowest RMSE.
link a local phenomenon and an averaged model grid cell. It is a better approach than the model tuning, sometimes efficient, but not able to explain the physics and often limited to a specific model, with its own parameterizations and resolution. The model tuning is also systematic where the change proposed in this study varies in each model grid cell, adding realism to the system. A potential future direction could be the convective cold pools, known to increase mineral dust emissions very locally and certainly missing in many regional models.

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the principal investigators and their staff for establishing and maintaining the AERONET sites used in this study.

References


FIG. 10. Aerosol Size Distribution compared between the AERONET inversions and the CHIMERE modeled concentrations.


