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Surface Winds and Dust Biases in Climate Models

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Key Points:

- Climate models exhibit large errors in dust emitted from North Africa
- These dust errors are due to biases in modeled surface winds⁴
- Similar errors in MERRA-2 dust stem from biases in MERRA-2 surface winds

Abstract

An analysis of North African dust from models participating in the Fifth Climate Models Intercomparison Project (CMIP5) suggested that, when forced by observed sea surface temperatures, these models were unable to reproduce any aspects of the observed year-to-year variability in dust from North Africa. Consequently, there would be little reason to have confidence in the models' projections of changes in dust over the 21st century. However, no subsequent study has elucidated the root causes of the disagreement between CMIP5 and observed dust. Here I develop an idealized model of dust emission and then use this model to show that, over North Africa, such biases in CMIP5 models are due to errors in the surface wind fields and not due to the representation of dust emission processes. These results also suggest that because the surface wind field over North Africa is highly spatially autocorrelated, intermodel differences in the spatial structure of dust emission have little effect on the relative change in year-to-year dust emission over the continent. I use these results to show that similar biases in North African dust from the NASA Modern Era Retrospective analysis for Research and Applications (MERRA) version 2 surface wind field biases, but that these wind biases were not present in the first version of MERRA.

1 Introduction

Mineral aerosols, otherwise referred to as dust, is likely the most abundant aerosol in the atmosphere [Kok *et al.*, 2017] and has a role in many components of the coupled climate system. For example, dust emission is dependent on surface processes ranging from geomorphic evolution [Washington *et al.*, 2006] to the accumulation of fine sediment in an alluvial fan after a rain storm [Washington *et al.*, 2003]. Once airborne dust can alter the hydrological cycle by direct heating of the atmosphere and thus altering of lapse rates [e.g., Doherty and Evan, 2014], or by acting as an ice nuclei and enhancing precipitation rates [e.g., Creamean *et al.*, 2013]. As another example, due its mineralogy, dust deposition can represent an important source of nutrients to remote ecosystems [Das *et al.*, 2013]. Since dust affects—and is affected by—a multitude of climate processes, one can easily make the case that representing forced and unforced changes in dust emission, transport and deposition (i.e., the dust cycle) is critical in order to improve understanding of past and future climate change.

So how accurate are state-of-the-art climate models in terms of representing the dust cycle? Since roughly half of all planetary dust is emitted from the Sahara [Engelstaedter *et al.*, 2006], North Africa represents a reasonable location to start to address this question. A study of North African dust as simulated by models participating in the Fifth Climate Models Intercomparison Project (CMIP5) [Taylor *et al.*, 2012] demonstrated that state-of-the-art climate models generally failed to reproduce several key features of the dust cycle in this region [Evan *et al.*, 2014] (hereafter referred to as E14). Specifically, E14 examined dust in the CMIP5 output from the Atmospheric Model Intercomparison Project (AMIP) simulations. In these simulations, which span 1979–2005, sea surface temperature is prescribed and thus the modeled atmosphere is comparable to observations. E14 found that in the AMIP runs, and for all models, North African dust 1) was biased low in terms of column integrated mass, 2) was not positively and statistically significantly correlated to observed dust and 3) exhibited too little year-to-year variance. Furthermore, only one model reproduced the observed and statistically significant negative correlation between dust and Sahelian Rainfall [e.g., Prospero and Lamb, 2003].

Given the findings in E14, a logical next question to ask is what is the source of such biases? Disparities between models and observations, particularly in terms of inter-annual variability, could be stem from the process of emission, transport or deposition. However, E14 found that the models were very consistent in terms of the relationship between emission from North Africa and column integrated mass over the tropical North

Atlantic, suggesting a high level of intramodel agreement in terms of the physical processes governing the fate of dust once it is lofted into the atmosphere. Therefore, a more likely culprit for the disparity between models and observations is the process of emission, particularly as the process of dust emission is non-linear and dependent upon surface morphology, mineralogy, vegetation cover and type and soil moisture [Kok *et al.*, 2012]. Furthermore, E14 found a high level of disagreement in the spatial structure of long-term mean dust emission in CMIP5 models. In other words, the models did not agree on the locations where dust emission from North African actually occurred.

A recent study of North African dust showed that over the hyperarid Sahara desert, dust emission is, to first order, simply a function of wind speed, and that on monthly time scales the relationship between surface wind speed and emission could be linearized [Evan *et al.*, 2016]. Here I formalize and then use this simplification of the process of dust emission over North Africa to elucidate the source of the disparity between CMIP5 models and observations. I then utilize the same approach to understand the source of a similar disparity in dust from a new reanalysis product, the NASA Modern Era Retrospective analysis for Research and Applications version 2 (MERRA-2) Aerosol Reanalysis [Randles *et al.*, 2017].

2 Data and Methods

I start by considering that dust emission (E) at time t is a function of the state of the physical climate system (X) at that same time, such that

$$E(t) = f(X(t)) \quad (1)$$

where over time changes in E are generalized by

$$\frac{\delta E}{\delta t} = \frac{\partial E}{\partial X} \frac{\delta X}{\delta t} \quad (2)$$

It is somewhat obvious to state that in order to effectively simulate the temporal variability of dust it is necessary to accurately represent changes in the state of the physical climate system, and that dust emission must have appropriate sensitivities to the state of the climate. Additionally, $\partial E / \partial X$, which in a model is represented by an emission parameterization scheme, can be decomposed into

$$\frac{\partial E}{\partial X} = \frac{\partial E}{\partial \tau} + \frac{\partial E}{\partial w} + \frac{\partial E}{\partial V} + \frac{\partial E}{\partial M} \quad (3)$$

where τ is the surface wind stress, w is surface soil moisture, V is fractional vegetation cover and M is the amount of erodible material. Combining (2) and (3), and noting that τ is often represented by a term proportional to the cube of the surface wind speed (U) [Marshall *et al.*, 2011], and ignoring changes in near-surface air density,

$$\frac{\delta E}{\delta t} = \frac{\partial E}{\partial U} \frac{\delta U}{\delta t} + \frac{\partial E}{\partial w} \frac{\delta w}{\delta t} + \frac{\partial E}{\partial V} \frac{\delta V}{\delta t} + \frac{\partial E}{\partial M} \frac{\delta M}{\delta t} \quad (4)$$

thus for a small change in emission for a small change in time is dependent upon the emission sensitivities to wind, soil moisture, vegetation cover and the availability of erodible material, as well as the temporal evolution of each.

As noted above, North Africa is a special case where E is, to first order, and on long time scales, not dependent upon w and V , as the Sahara is practically always dry and unvegetated. If one assumes that M is constant in time at a given location, which is valid

for major source regions in North Africa [*Washington et al.*, 2006; *Prospero et al.*, 2002], then (4) can be integrated to give

$$E' = \frac{\partial E}{\partial U} U' \quad (5)$$

where the primes indicate that only perturbations about the mean values for the terms in (5) are of interest, which allows one to ignore the constant of integration. Here, $\partial E / \partial U$ has units of mass flux per unit wind speed.

The linearized equation for North African dust emission in (5) can also be obtained by considering a typical model parameterization for dust emission. For example, using the formulation in Gillette and Passi (1988),

$$E = CSU^2(U - U_t) \quad (6)$$

where U_t is a windspeed threshold such that $E = 0$ for $U < U_t$, C is a dimensionalization factor and S is the so-called source function, which is an empirically derived factor that increases with the increasing availability of deflatable material M . In (6) the dependency of E on w and V is represented by the choice of U_t . Given that S and C are constants, linearizing (6) via a Taylor series expansion about $U = U_t$ gives

$$E' = CS(U_t^2 U' - U_t^3) \quad (7)$$

where only the first two terms in the expansion are retained and again the primes indicate deviations about the mean values of emission and windspeed. Eq (7) can then be rearranged and then solved via linear regression of E onto U to give a result identical to that in (5), where

$$\partial E / \partial U = CSU_t^2 \quad (8)$$

It is possible to obtain similar results using the vertical dust flux parameterization of *Marticorena and Bergametti* [1995] or the formulation in *Kok et al.* [2014, Eq 3].

Expanding about U_t is a reasonable choice since at the extreme where the average $U \ll U_t$ one would expect no emission and thus $\partial E / \partial U$ would be zero. At the other extreme, where the average $U \gg U_t$, one would also expect no emission, averaged over long time scales, since any available erodible material would be quickly depleted. With regards to the definition of $\partial E / \partial U$, substituting (8) into (5) suggests that emission anomalies are proportional to U_t^2 , which runs counter to understanding of the physical processes governing dust emission, underscoring the importance of S in dust emission parameterizations.

As (5) will be used to diagnose errors in modeled North African dust, dust emission and surface windspeed data will be used in this analysis. In order to validate the analysis methodology I will first consider dust emission from a 1982–2008 run of the Goddard Earth Observing System global 3-D chemical transport model (GEOS-Chem) that was driven by assimilated meteorology from the NASA Modern Era Retrospective analysis for Research and Applications version 1 (MERRA) [*Rienecker et al.*, 2011] from the Goddard Earth Observing System of the NASA Global Modeling and Assimilation Office (GMAO) *Ridley et al.* [2014] (hereafter R14). In R14 dust emission is based upon the Dust Entrainment and Deposition scheme [*Zender et al.*, 2003] and dust sources are from *Ginoux et al.* [2001]. I use this study since the output from this simulation was shown to be in good agreement with an observation-based record of dust in the region [*Evan*

Table 1. CMIP5 Models Used and Correlation with R14

Model Name	r-value (p-value) ^a
CSIRO-Mk3-6-0	0.08 (0.69)
CanAM4	-0.44 (0.02)
HadGEM2-A	0.06 (0.75)
MIROC5	-0.33 (0.09)
MRI-CGCM3	-0.41 (0.04)
NorESM1-M	0.33 (0.10)

^aBased on annual time series.

and Mukhopadhyay, 2010]. Dust emission data was only available for six CMIP5 models (Table 1) and so the analysis will be limited to the output from their corresponding AMIP runs. Lastly, I will examine dust emission and surface windspeeds from MERRA-2 [Gelaro *et al.*, 2017; Randles *et al.*, 2017]. In MERRA-2, dust is simulated with the Goddard Chemistry, Aerosol, Radiation, and Transport model [Chin *et al.*, 2002; Colarco *et al.*, 2010] using a representation of dust sources from Ginoux *et al.* [2001] and the emission parameterization scheme of Marticorena and Bergametti [1995].

In this paper the statistical significance (p-values) of correlation coefficients is calculated via a two-tailed t-test, and the uncertainty in linear trends is reported at the 95% level.

3 Results

I firstly demonstrate that over North Africa, and on interannual time scales, the process of dust emission can be represented by (6), using output from the model simulation described in R14. First, a map of $\partial E / \partial U$ (8) over North Africa was created by calculating the coefficient of the linear regression of modeled dust emission anomalies (E) onto MERRA surface windspeed anomalies (U), which has units of mass flux per unit wind speed, using data from the model simulations from R14 (Fig 1a). Here there are two regions where the mass flux is most sensitive to wind speed, the first is the Bodele Depression (approximately 15°N and 15°E) and the second is within eastern Mauritania (approximately 18°N and -5°E), both of which are thought to be important dust sources [Goudie and Middleton, 2001].

Next, I reconstruct a time series of E by projecting monthly mean maps of U' anomalies from MERRA onto the map of $\partial E / \partial U$ in (Fig 1a) and sum these values over the North Africa and over each year. The region used for this calculation is that shown in Figure 1, which spans -20° to 40°E and 10° to 35°N. The resultant time series of annual North African dust emission (Fig 2a, red) is then compared with dust emission from R14 (Fig 2a, blue). Both time series show a decline in dust emission that is consistent observational records [Evan and Mukhopadhyay, 2010]. While the idealized representation is not a perfect match to the actual model output, the two are highly correlated with an r-value of 0.85 (p-value < 0.01) and the downward linear trends for each are not statistically difference; the R14 trend is $-7.7 \pm 2.5 \text{ Tg yr}^{-1}$ and the reconstructed trend is $-4.5 \pm 1.8 \text{ Tg yr}^{-1}$. The agreement between the two interannual time series of emission validates the use of Eq (5) to estimate dust emission, on interannual time scales, if the surface windspeeds and emission sensitivities to those windspeeds are known. We repeated this analysis for the CMIP5 models, where the multimodel mean emission and estimated emission (Fig 2b) are correlated with an r-value of 0.73 (p-value < 0.01).

Figure 1. Maps of $\partial E/\partial U$ calculated from model output. All maps are calculated via the linear regression of wind speed anomalies onto emission anomalies. Scaling factors have been applied to the maps (indicated in the inset boxes) to simplify model intercomparison. The model names are indicated above each map.

I next calculate maps of $\partial E/\partial U$ using monthly mean anomalies of E and U from the six CMIP5 models examined (Figs 1b–g). Here, the models show some divergence in terms of the spatial structure and the magnitude of the emission sensitivity to the surface winds. For example, only one model shows a high (relative) emission sensitivity in the vicinity of the Bodele Depression (Fig 1g), similar to that for R14 (Fig 1a), whereas all of the other CMIP5 models show a high sensitivity just to the northwest of this region (Figs 1b–f). Three of the CMIP5 models have a region of high emission sensitivities in the northwestern corner of North Africa and along the Mediterranean coast (Figs 1b,c,f), and two other models have the highest emissions sensitivities far to the east (Fig 1e,g). In Figure 1 the values of $\partial E/\partial U$ are scaled so that the largest value of $\partial E/\partial U$ for each model is equal to that for R14 (inset boxes). For five of the CMIP5 models these scaling values are within an order of magnitude of unity, suggesting that the magnitude of the emission sensitivities are in agreement. The scaling factor for the NorESM1-M model (Fig 1g) is 3.8×10^3 , which is due to the fact that the variance in dust emission in this model is far smaller than that for the other models (Fig S1a). Also shown is the multimodel mean map of $\partial E/\partial U$ (Fig 1h); due to the general lack of agreement between the models the multimodel mean is relatively homogeneous across North Africa.

The multimodel mean time series of annual North African dust emission is not well correlated with the time series of emission from R14 (Fig 2b), where the correlation r -

Figure 2. Time series of model emission. In each panel are plotted a time series of emission as simulated by the model and an estimate of emission calculated by projecting windspeed anomalies onto the corresponding maps of $\partial E/\partial U$ (Fig 1). Here, CMIP5 refers to the multimodel mean emission or estimated emission from the CMIP5 AMIP experiments for the models indicated in Table 1. All time series are averages over -20° to 40°E and 10° to 35°N .

value is -0.27. Similarly, none of the correlation coefficients for the individual model time series of emission (Fig S1) are statistically significant and positive (Table 1). These results are very similar to those reported in E14, which is not surprising given that the interannual time series of dust in R14 is very similar to observations (Figure 3 in R14). It is tempting to assume that differences in emission amongst the models, and between the models and R14, are due to the differences in the sensitivities of emission to windspeed (Fig 1). We test this assumption by calculating the emission via projection of CMIP5 models' U onto the R14 map of $\partial E/\partial U$ (Fig 1a). The resultant time series of North African dust emission (Fig 2c, blue) is also uncorrelated with the time series of emission from R14 (r-value = -0.19), and is instead positively and significantly correlated with the CMIP5 multimodel mean time series of emission (r-value = 0.66, p-value < 0.01). Thus, the spatial structure of $\partial E/\partial U$ appears to be of second-order importance with regards to affecting year-to-year changes in E .

I lastly calculate emission by projecting U from R14 onto the CMIP5 multimodel mean $\partial E/\partial U$ (Fig 1h). The resultant multimodel mean E (Fig 2c, red) is very similar to the time series of E from R14 (Fig 2c, black); the two are positively and significantly correlated (r-value = 0.79, p-value < 0.01). This result suggests that the temporal evolution of the surface windspeeds is of primary importance with regards to correctly representing the interannual variability of dust emission over North Africa. This result is consistent

with *Evan et al.* [2016]; soil moisture and ground cover appear to be of little consequence in shaping the year-to-year changes in dust emitted from the region.

4 Conclusions

It is somewhat surprising that the spatial structure of $\partial E/\partial U$ has little effect on year-to-year changes in dust emitted from North Africa. Presumably this is because the surface windspeeds over the continent are spatially correlated. An analysis of annual mean wind fields from R14 (MERRA) suggest that the average distance at which the wind fields are no longer correlated (defined as where the r-value drops to $= e^{-1}$) is approximately 700 km (Fig S2). However, correlation maps of monthly mean windspeeds over regions where the R14 $\partial E/\partial U$ is very large (Fig 1a) suggest that this decorrelation distance is much larger for dust emitting regions (Fig S3). For example, the correlation map of annual mean U over the Bodele depression shows a wide swath of r-values greater than e^{-1} that extend upwind and downwind of the depression (Fig S3a). This result suggests that the interannual variability of surface winds and dust emission over the Sahara is dominated by large-scale meteorological processes that influence the larger region. These results also suggest that in order to improve dust in climate models the surface wind speeds over remote desert regions must be realistic. Here, only one CMIP5 model had surface winds (averaged over North Africa) that were positively and significantly correlated with those from MERRA (NorESM1-M, r-value = 0.51, p-value < 0.01), which is also the model whose dust emission was the best correlated with R14 (r-value = 0.33, p-value = 0.10, Table 1). The causes of the poor representation of the surface flow in CMIP5 models is beyond the scope of the paper. However, an initial analysis suggests that above the boundary layer, windspeeds in CMIP5 models are in agreement with reanalysis (not shown), suggesting that the errors may be rooted in the treatment of boundary layer processes.

The idealized treatment of dust emission presented here is useful beyond the examination of CMIP5 models; I lastly utilize these results to compare dust in R14 and MERRA-2. Dust in R14 and in MERRA-2 are both simulated with the Mineral Dust Entrainment and Deposition (DEAD) scheme [Zender *et al.*, 2003]. The main difference between the two simulations is in the meteorology forcing each; winds from MERRA are used in the R14 simulations and winds from MERRA-2 drive the MERRA-2 aerosols. Since dust emission rates were not available for MERRA-2 I use dust surface concentration data ($C_{d,s}$), which, over North Africa, is highly correlated with emission rates (for R14, r-value = 0.93, p-value < 0.01). The interannual time series of average North African surface dust concentration ($C_{d,s}$) from R14 and MERRA-2 have little in common (Fig 3a). The correlation between the two series is negative (-0.19), and the linear trend in R14 dust is negative and statistically significant. Conversely, the trend for MERRA-2 is positive and statistically significant. Based on the results presented in this paper it is likely that these differences in dust stem from differences in surface wind speeds, and the correlations between U and $C_{d,s}$ from R14 and MERRA-2 are positive and significant (r-value = 0.75 and 0.78, respectively, both with p-values < 0.01). While the MERRA and MERRA-2 time series of U averaged over North Africa are statistically significantly correlated (r-value = 0.37, p-value = 0.05), their respective trends in U are statistically different, where there is a statistically significant negative trend in R14 (MERRA) U and no significant trend in MERRA-2 U (Fig 3b).

While not conclusive, the similarity between the differences in surface dust concentration and windspeeds suggests that changes in windspeeds between MERRA and MERRA-2 have resulted in an unrealistic interannual time series of North African dust in MERRA-2. Understanding the nature of the differences in the MERRA windspeeds is beyond the scope of this paper. However, it is worth mentioning that two major differences between the reanalysis are the quantity of data assimilated (Figure 1 in *Gelaro et al.*

Figure 3. Figure 3. Time series of dust and winds in R14 and MERRA-2. Plotted in 3a are time series of the dust surface concentration $C_{d,s}$ from R14 and MERRA-2, averaged over North Africa, and their respective linear trends, in units of dust concentration per decade ($\mu\text{g m}^{-3} \text{ d}^{-1}$). Also plotted are time series of the surface wind speeds (U) from R14 and MERRA-2, where the winds in R14 are from MERRA, and their respective trends, in units of windspeed per decade ($\text{m s}^{-1} \text{ d}^{-1}$). Show in the legends are the 95% uncertainty levels of the linear trends.

[2017]) and a change in the treatment of surface layer turbulence over land [Molod *et al.*, 2015].

Lastly, I again note that this idealized model is only applicable to regions like the Sahara, which are characterized as barren and having little to no precipitation. Furthermore, the results presented here are for examining interannual variability of dust. A similar analysis of output from R14 and CMIP5 models, but using seasonal data, did show similar results (Fig S4). Thus, such a highly idealized approach to studying the processes governing emission may only be valid on seasonal and longer time scales.

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References

Chin, M., P. Ginoux, S. Kinne, O. Torres, B. N. Holben, B. N. Duncan, R. V. Martin, J. A. Logan, A. Higurashi, and T. Nakajima (2002), Tropospheric aerosol optical thickness from the gocart model and comparisons with satellite and sun photometer measurements, *Journal of the atmospheric sciences*, 59(3), 461–483.

- Colarco, P., A. da Silva, M. Chin, and T. Diehl (2010), Online simulations of global aerosol distributions in the nasa geos-4 model and comparisons to satellite and ground-based aerosol optical depth, *Journal of Geophysical Research: Atmospheres*, 115(D14).
- Creamean, J. M., K. J. Suski, D. Rosenfeld, A. Cazorla, P. J. DeMott, R. C. Sullivan, A. B. White, F. M. Ralph, P. Minnis, J. M. Comstock, et al. (2013), Dust and biological aerosols from the sahara and asia influence precipitation in the western us, *Science*, 339(6127), 1572–1578.
- Das, R., A. Evan, and D. Lawrence (2013), Contributions of long-distance dust transport to atmospheric p inputs in the yucatan peninsula, *Global Biogeochemical Cycles*, 27(1), 167–175.
- Doherty, O. M., and A. T. Evan (2014), Identification of a new dust-stratocumulus indirect effect over the tropical north atlantic, *Geophysical Research Letters*, 41(19), 6935–6942.
- Engelstaedter, S., I. Tegen, and R. Washington (2006), North african dust emissions and transport, *Earth-Science Reviews*, 79(1), 73–100.
- Evan, A. T., and S. Mukhopadhyay (2010), African dust over the northern tropical atlantic: 1955–2008, *Journal of Applied Meteorology and Climatology*, 49(11), 2213–2229.
- Evan, A. T., C. Flamant, S. Fiedler, and O. Doherty (2014), An analysis of aeolian dust in climate models, *Geophysical Research Letters*, 41(16), 5996–6001.
- Evan, A. T., C. Flamant, M. Gaetani, and F. Guichard (2016), The past, present and future of african dust, *Nature*, 531(7595), 493–495.
- Gelaro, R., W. McCarty, M. J. Suárez, R. Todling, A. Molod, L. Takacs, C. A. Randles, A. Darmenov, M. G. Bosilovich, R. Reichle, et al. (2017), The modern-era retrospective analysis for research and applications, version 2 (merra-2), *Journal of Climate*, 30(14), 5419–5454.
- Ginoux, P., M. Chin, I. Tegen, J. M. Prospero, B. Holben, O. Dubovik, and S.-J. Lin (2001), Sources and distributions of dust aerosols simulated with the gocart model, *Journal of Geophysical Research: Atmospheres*, 106(D17), 20,255–20,273.
- Goudie, A., and N. Middleton (2001), Saharan dust storms: nature and consequences, *Earth-Science Reviews*, 56(1), 179–204.
- Kok, J., N. Mahowald, G. Fratini, J. Gillies, M. Ishizuka, J. Leys, M. Mikami, M.-S. Park, S.-U. Park, R. Van Pelt, et al. (2014), An improved dust emission model—part 1: Model description and comparison against measurements, *Atmospheric Chemistry and Physics*, 14(23), 13,023–13,041.
- Kok, J. F., E. J. Parteli, T. I. Michaels, and D. B. Karam (2012), The physics of wind-blown sand and dust, *Reports on Progress in Physics*, 75(10), 106,901.
- Kok, J. F., D. A. Ridley, Q. Zhou, R. L. Miller, C. Zhao, C. L. Heald, D. S. Ward, S. Albani, and K. Haustein (2017), Smaller desert dust cooling effect estimated from analysis of dust size and abundance, *Nature Geoscience*.
- Marshall, J. H., P. Knippertz, N. S. Dixon, D. J. Parker, and G. Lister (2011), The importance of the representation of deep convection for modeled dust-generating winds over west africa during summer, *Geophysical Research Letters*, 38(16).
- Martcorena, B., and G. Bergametti (1995), Modeling the atmospheric dust cycle: 1. design of a soil-derived dust emission scheme, *Journal of Geophysical Research: Atmospheres*, 100(D8), 16,415–16,430.
- Molod, A., L. Takacs, M. Suarez, and J. Bacmeister (2015), Development of the geos-5 atmospheric general circulation model: evolution from merra to merra2, *Geoscientific Model Development*, 8(5), 1339–1356.
- Prospero, J. M., and P. J. Lamb (2003), African droughts and dust transport to the caribbean: Climate change implications, *Science*, 302(5647), 1024–1027.
- Prospero, J. M., P. Ginoux, O. Torres, S. E. Nicholson, and T. E. Gill (2002), Environmental characterization of global sources of atmospheric soil dust identified with the nimbus 7 total ozone mapping spectrometer (toms) absorbing aerosol product, *Reviews of geophysics*, 40(1).

- Randles, C., A. M. da Silva, V. Buchard, P. Colarco, A. Darmenov, R. Govindaraju, A. Smirnov, B. Holben, R. Ferrare, J. Hair, et al. (2017), The merra-2 aerosol reanalysis, 1980 onward. part i: System description and data assimilation evaluation, *Journal of Climate*, 30(17), 6823–6850.
- Ridley, D., C. Heald, and J. Prospero (2014), What controls the recent changes in african mineral dust aerosol across the atlantic?, *Atmospheric Chemistry and Physics*, 14(11), 5735–5747.
- Rienecker, M. M., M. J. Suarez, R. Gelaro, R. Todling, J. Bacmeister, E. Liu, M. G. Bosilovich, S. D. Schubert, L. Takacs, G.-K. Kim, et al. (2011), Merra: Nasa’s modern-era retrospective analysis for research and applications, *Journal of climate*, 24(14), 3624–3648.
- Taylor, K. E., R. J. Stouffer, and G. A. Meehl (2012), An overview of cmip5 and the experiment design, *Bulletin of the American Meteorological Society*, 93(4), 485–498.
- Washington, R., M. Todd, N. J. Middleton, and A. S. Goudie (2003), Dust-storm source areas determined by the total ozone monitoring spectrometer and surface observations, *Annals of the Association of American Geographers*, 93(2), 297–313.
- Washington, R., M. Todd, G. Lizcano, I. Tegen, C. Flamant, I. Koren, P. Ginoux, S. Engelstaedter, C. Bristow, C. Zender, et al. (2006), Links between topography, wind, deflation, lakes and dust: The case of the bodélé depression, chad, *Geophysical Research Letters*, 33(9).
- Zender, C. S., H. Bian, and D. Newman (2003), Mineral dust entrainment and deposition (dead) model: Description and 1990s dust climatology, *Journal of Geophysical Research: Atmospheres*, 108(D14).