JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 108, NO. D12, 4352, doi:10.1029/2002JD002821, 2003

# Interannual variability in atmospheric mineral aerosols from a 22-year model simulation and observational data

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Received 2 August 2002; revised 21 January 2003; accepted 11 March 2003; published 19 June 2003.

[1] Mineral aerosols are important atmospheric constituents owing to their interactions with climate and biogeochemistry. The interannual variability in atmospheric mineral aerosols is evaluated using a model simulation of 1979–2000 and mineral aerosol observations. Overall, the variability in monthly means between different years is not as large as the variability within a month for column amount, surface concentration, and deposition fluxes. The magnitude of the variability predicted in the model varies spatially and appears similar to that seen in the available observations, although the model is not always able to simulate observed high- and low-dust years. The area over which the interannual variability in the observing station data should be representative is estimated in the model simulation and is shown to be regional in extent. However, correlations between modeled surface concentrations at the stations and modeled deposition in the surrounding region is often low, suggesting that the observations of the variability of surface concentrations are difficult to extrapolate to variability in regional deposition fluxes. The correlations between modeled monthly mean optical depth and modeled deposition or mobilization are low to moderate (0.2–0.6) over much of the globe, indicating the difficulty of estimating mobilization or deposition fluxes from satellite retrievals of optical depth. In both the model and observations there are relationships between climate indices (e.g., North Atlantic Oscillation, El Niño, and Pacific Decadal Oscillation) and dust, although a 22-year simulation is not long enough to well characterize this relationship. In this model, simulation of 1979–2000, dust concentration variability appears to be dominated by transport variability and/or transport and source covariance rather than source strength variability. *INDEX TERMS:* 0305 Atmospheric Composition and Structure: Aerosols and particles (0345, 4801); 0315 Atmospheric Composition and Structure: Biosphere/atmosphere interactions; 0368 Atmospheric Composition and Structure: Troposphere—constituent transport and chemistry; 1615 Global Change: Biogeochemical processes (4805); *KEYWORDS:* mineral aerosols, interannual variability, desert dust

**Citation:** Mahowald, N., C. Luo, J. del Corral, and C. S. Zender, Interannual variability in atmospheric mineral aerosols from a 22-year model simulation and observational data, *J. Geophys. Res.*, *108*(D12), 4352, doi:10.1029/2002JD002821, 2003.

## 1. Introduction

[2] Mineral aerosols are thought to impact the radiative budget due to absorption and scattering of solar and infrared radiation [e.g., *Miller and Tegen*, 1998], to modify atmospheric chemistry through heterogeneous reactions and photolysis rates [e.g., *Dentener et al.*, 1996], and to impact terrestrial and ocean biogeochemistry when deposited onto the ground or ocean [e.g., *Chadwick et al.*, 1999; *Martin*, 1990]. Observations of atmospheric concentrations of mineral aerosols suggest that there is substantial interannual variability [e.g., *Prospero and Nees*, 1986]. In addition, the fraction of desert dust particles which are produced to human interactions are unknown. *Tegen and Fung* [1995] argued that up to 50% of current atmospheric loading is due to disturbed sources (including natural vegetation shifts and human land use changes), while *Prospero et al.* [2002] and *Ginoux et al.* [2001] argue that most of the sources of desert dust are naturally occurring. *Mahowald et al.* [2002] argue that current atmospheric data are insufficient to discriminate between a natural topographic low source, a disturbed source, and a land use source in North Africa. In order to make accurate estimates of the anthropogenic radiative forcing of

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0148-0227/03/2002JD002821

**Table 1.** Correlation Between Interannual Variability in Model and Observations[a]

| | Monthly Correlation | Monthly Anomaly Correlation | Annual Correlation | Number of Months of Data | Daily Averaged Correlation |
|---|---|---|---|---|---|
| Barbados | **0.66** (**0.77**) | **0.46** (**0.52**) | **0.38** (**0.45**) | 260 | 0.51 (0.63) |
| Izana | **0.64** (**0.74**) | **0.51** (**0.55**) | **0.64** (0.63) | 104 | 0.31 (0.60) |
| Bermuda | **0.83** (**0.86**) | **0.74** (**0.47**) | **0.84** (0.62) | 108 | 0.49 (0.61) |
| Miami | **0.72** (**0.62**) | **0.39** (**0.23**) | 0.03 (−0.12) | 227 | 0.65 (0.51) |
| Midway | **0.64** (**0.76**) | **0.27** (0.18) | **−0.41** (−0.35) | 109 | 0.84[b] (0.57) |
| Hawaii | **0.74** (**0.86**) | **0.38** (**0.47**) | **0.48** (0.27) | 62 | 0.46[b] (0.77) |
| Enewtak | **0.40** (**0.63**) | −0.00 (0.18) | **0.71** (0.70) | 43 | 0.81[b] (0.82) |
| Funafuti | −0.08 (0.01) | −0.02 (0.03) | NAN (0.20) | 40 | |
| Mace Head | **0.34** (**0.49**) | **0.27** (**0.27**) | **−0.53** (−0.60) | 59 | |
| Norfolk | 0.09 (0.23) | 0.30 (0.14) | 0.39 (0.09) | 44 | |

[a]Rank correlations are in parentheses, and 95% statistically significant values are boldfaced. NAN, not a number.
[b]Station only has weekly averaged data, so weekly averaged correlations are shown.

mineral aerosols, we need to understand the natural fluctuations in desert dust. *Tegen and Miller* [1998] conducted a 15-year interannual variability study in the Goddard Institute of Space Sciences General Circulation Model (GCM) assuming that all desert regions were sources and showed that transport variations produce most of the interannual variability in their model. Here we look in more detail at the interannual variability in a 22-year simulation from the Dust Entrainment and Deposition (DEAD) dust module, Model of Atmospheric Transport and Chemistry (MATCH) offline chemical transport model, using National Center for Environmental Prediction (NCEP)/National Center for Atmospheric Research reanalysis. Comparisons between simulations from this dust model and available observations show that the climatology of the 22-year simulation is roughly consistent with available observations [*Luo et al.*, 2003]. In this companion paper we focus on the interannual variability of the simulation.

[3] The paper is organized as follows: In section 2 we briefly describe the model simulations used in the comparison and previous comparisons of the model against observations. Section 3.1 compares model and observed interannual variability at in situ sites as well as from satellite observations. Section 3.2 compares the amount of variability in the model and observations (in situ and satellite). Section 3.3 evaluates the correlation of climate indices with desert dust in model and observations at the stations, while section 3.4 expands this to look at spatial correlations in the model and the climate indices. Section 3.5 focuses on the correlations between different sites in the model and observations, while section 3.6 uses the model results to evaluate the representativeness of the station data and satellite data. Section 3.7 evaluates the role of interannual variability in sources in controlling interannual variability in concentrations at the stations. Finally, section 4 summarizes the results of the study.

## 2. Model Description

[4] In this study we use the 22-year model simulation described by *Luo et al.* [2003]. The DEAD dust module [*Zender et al.*, 2003] (also available at www.ess.icu.edu/~zender) is based on the wind tunnel studies of *Iversen and White* [1982], *Marticorena and Bergametti* [1995], *Gillette et al.* [1998], and *Fecan et al.* [1999] and includes mobilization (entrainment of dust into the atmosphere), and dry and wet deposition. The source areas are defined as in *Ginoux et al.* [2001] to be dry, unvegetated regions that have relatively low topography. The transport model is the MATCH off-line chemical transport model [*Rasch et al.*, 1997], which has been shown to work well with NCEP reanalysis data sets [*Mahowald et al.*, 1997]. The meteorological data used to drive the models is the NCEP reanalysis [*Kalnay et al.*, 1996; *Kistler et al.*, 2001]. Evaluations of this data set suggest that it is most robust after 1979 [e.g., *Santer et al.*, 2000] but that there are problems during the 1979–2000 period, especially in the hydrological cycle and in the tropics [e.g., *Trenberth and Guillemot*, 1998; *Trenberth et al.*, 2001], similar to other reanalyses and models. For this study we simulated the dust cycle in the atmosphere from 1979 to 2000. Optical depths are calculated following *Zender et al.* [2003].

[5] The model described above was compared to available climatological observations of *Luo et al.* [2003], and we summarize the results here. The model is able to capture the monthly mean concentrations at surface stations globally but had more difficulty at several stations in the Southern Hemisphere. Comparisons to deposition observations, both in situ and marine sediment cores, also show rough consistency with the model simulations over 4 orders of magnitude in deposition fluxes. Aerosol optical thicknesses predicted in the model appear consistent with available satellite and Aerosol Robotic Network (AERONET) observations. The model daily (or weekly) averaged variability was compared to observations, and from this analysis it appears that the model is often able to capture specific dust events but that the timing or the magnitude of the event may be slightly incorrect in the model. Overall, the model simulation compares as well with available observations as similar modeling studies [e.g., *Ginoux et al.*, 2001; *Tegen et al.*, 2002], especially in the relatively well-observed Northern Hemisphere, but there are problems with the magnitude and seasonality of the dust at a few stations in the Southern Hemisphere.

## 3. Results

### 3.1. Comparisons of Interannual Variability With Observations

[6] At least 2 years of measurement data are available at 10 in situ measurement sites, shown in Table 1. The latitude and longitude of these sites are given in Figure 1, and the data are made available to us courtesy of D. Savoie, J. Prospero, and R. Arimoto [i.e., *Prospero and Nees*, 1986; *Prospero*, 1990; *Prospero et al.*, 1996; *Arimoto et al.*, 1990, 1997]. These data

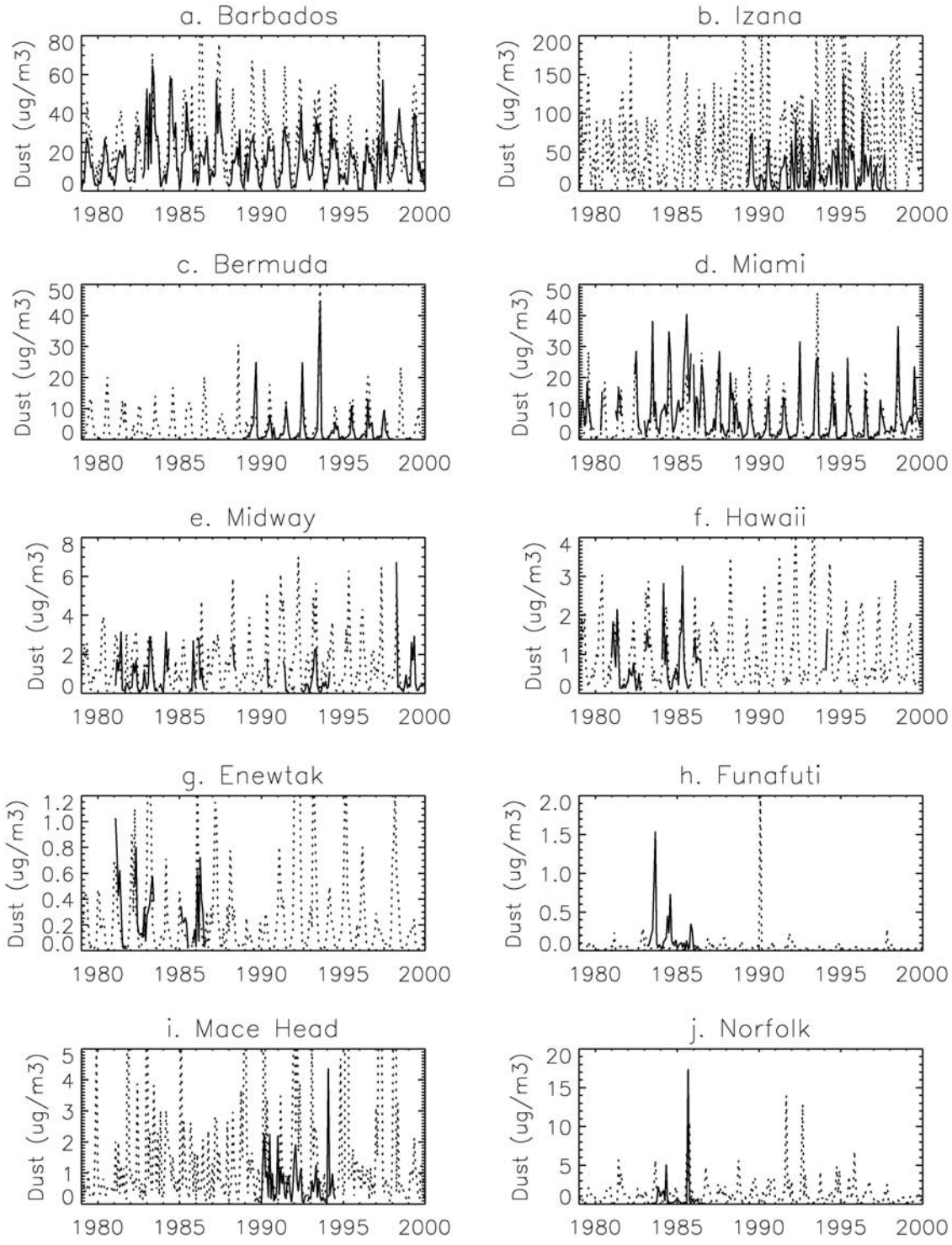



**Figure 1.** Observed (solid lines) and modeled (dashed lines) monthly mean concentrations at (a) Barbados (13°N, 59°W), (b) Izana (28°N, 16°W), (c) Bermuda (32°N, 65°W), (d) Miami (26°N, 80°W), (e) Midway (28°N, 177°W), (f) Hawaii (21°N, 158°W), (g) Enewtak (11°N, 162°E), (h) Funafuti (8°S, 179°W), (i) Mace Head (53°N, 10°W), and (j) Norfolk (29°S, 168°E).

represent concentrations at one point and may not be representative of an entire grid cell. However, because they are usually located on islands and attempt to sample clean marine air, we assume for this study that they are representative of the grid cell size area. This does create a potentially important difference between the model and observations, however, since observational sites only report concentrations when the winds are from the marine sector, while the model results are under all wind conditions.

[7] A comparison of the monthly mean concentrations from the observations and the model predictions is shown in Figure 1 for 1979–2001. The correlations of the monthly

average concentrations between the model and observations are shown in Table 1. The correlation coefficient is a useful quantity in evaluating similarities between model and observations and is widely used in the literature. However, strictly speaking, the evaluation of the significance of the correlation coefficient requires that the distributions of both data to be Gaussian and that their joint probability distribution also be Gaussian [e.g., *Press et al.*, 1992]. In the case of the mineral aerosols evaluated here the distributions of daily mean, monthly mean, and annual mean concentrations, deposition, and column amounts are not Gaussian, and thus the assumptions used to develop statistical significance tests are not valid. In order to test for statistical significance, tests like the rank correlation (rank the values and then correlate the ranks) need to be undertaken [e.g., *Press et al.*, 1992]. Because of the widespread use of the correlation coefficient and its easy physical interpretation we will show correlation coefficients in this study and show statistical significance assuming that the distributions are Gaussian (which is a bad assumption). In fact, using rank correlations does not significantly change our interpretation of the results, so we only show or discuss rank correlations in section 1. In addition, statistical significance requires assumptions about the number degrees of freedom and autocorrelations within the data. In this study, we make the simple assumption that each monthly averaged dust concentration, mobilization, deposition, or column amount are independent. Of course, since dry years will tend to have more dust for the entire season or longer, this is probably not a good assumption. The caveats presented here imply that even when our results are statistically significant, we should interpret the results carefully.

[8] Overall, similar to that seen in the climatology [*Luo et al.*, 2003], the model is usually able to capture the strong seasonal cycle seen at observations stations, as seen in Table 1. The correlations and rank correlations are moderately high (0.6–0.8) for most of the stations, except for Southern Hemisphere stations such as Enewtak, Funafuti, and Norfolk, as well as the Mace Head, Ireland, station, where there are fewer months in the data record and which may contain contamination from small local sources not included in the simulation. The stations at which the model simulation compares the worst are also the stations which have the fewest months of data (also shown in Table 1). In addition, the Mace Head station only reports dust concentrations when the wind blows from the west, but the model averages include concentrations during transport from Europe. It is likely that North African dust is transported over Europe before being observed at the Mace Head station. Observations from the Funafuti site may not be as robust, owing to the very small concentrations and the possibility of contamination (J. Prospero, personal communication, 2002). Notice, however, that even with a rank correlation of 0.86 at Bermuda the model is only able to correctly predict ~60% of the variability in the ranks (correlation squared).

[9] Next we consider the monthly anomalies (monthly average minus the 22-year mean of the monthly average) and the ability of the model to predict not just the seasonal cycle but also the interannual variability. For most of this paper we consider the monthly anomaly (the deviation of the monthly average from the 22-year average for that month) in order to evaluate interannual variability. Correlations and rank correlations between the model and observations of the monthly anomalies are again shown in Table 1 and tend to be smaller than when we include the seasonal cycle. Correlations and rank correlations are significant at over half the sites, again with the largest problems in the data poor Southern Hemisphere, where our mean distribution is also the worst. Additionally, we consider the annual average concentrations predicted in the model and calculated from the observations (Table 1). In this case, the model is able to capture the interannual variability at only half the stations; notably, Miami and Midway are not well predicted considering the correlation coefficient, and neither Izana nor Bermuda are statically significantly correlated if we use the rank correlations. If one contrasts the correlation coefficients and rank correlation coefficients derived from daily averages and interannual variability, it appears that the model is just as capable of capturing individual events as of capturing interannual variability. We come back to the question of capturing interannual variability after looking at the variability in the model versus observations (section 3.2).

[10] Notice that in Table 1 the difference between the correlation coefficient and the rank correlations tend to be small and that assuming (incorrectly) that the correlation coefficient derives from Gaussian distribution results in values that are similarly statistically significant than using the more statistically robust rank correlation coefficient, except in the case of the correlation of the annual averages. Because of these similarities and for simplicity of showing the results, we will use correlation coefficients for the rest of the paper.

[11] Next we compare modeled column amount with available satellite data: Total Ozone Mapping Spectrometer (TOMS) Absorbing Aerosol Index (AI) and the advanced very high resolution radiometer (AVHRR). Both data sets have some problems in interpreting them, discussed in more detail elsewhere [e.g., *Cakmur et al.*, 2001; *Torres et al.*, 1998; *Mishchenko et al.*, 1995]. The TOMS AI is able to detect absorbing aerosols over land, but the AI is not only proportional to optical depth but also to altitude of the dust (i.e., dust close to the surface has a relatively weak TOMS AI response). This makes direct comparison difficult. We show results here from the TOMS AI between 1984 and 1990 since this period was the most stable (O. Torres, personal communication, 2001; similar to *Cakmur et al.* [2001]). Results over the whole time period tend to be slightly less clear than over this smaller, more robust time period and are not shown in the paper. To reduce cloud contamination, TOMS AI values are only included in the average when the spectral reflectance is <20%. In order to correct for some of these problems, *Torres et al.* [2002] combine the TOMS AI with model results (not from this dust model simulation but from *Ginoux et al.* [2001]) and some simple assumptions to infer an optical depth at 380 nm, called the TOMS aerosol optical depth (AOD). For this data set we make comparisons between 1983 and 2000 (with 1993–1996 having missing months and excluding 1991 and 1992 due to volcanic aerosols).

[12] The AVHRR satellite detects scattering aerosols, while mineral aerosol both scatter and absorb; thus there may be problems in interpreting the AVHRR optical depths for mineral aerosols. In addition, AVHRR retrievals are

sensitive to assumptions about the size of the aerosols [*Mishchenko et al.*, 1995]. *Cakmur et al.* [2001] have suggested that because of the large viewing pixel there are very few cloud-free data points per month at many locations, leading to potential biases in the monthly means. For the AVHRR comparison we use 1983, 1985–1990, and 1995–1998, owing to constraints on data availability and avoidance of volcanoes. The *Cakmur et al.* [2001] study suggested that the monthly averages derived from the TOMS AI may be more robust than AVHRR in regions with many clouds, which includes the region 0°–25°N across the Atlantic, which is unfortunately a large region where mineral aerosols dominate the aerosol optical depth. The satellite images are not without errors; as discussed by *Cakmur et al.* [2001], the uncertainty in the daily images (0.2 for TOMS AI and 0.04 for AVHRR optical depth) is roughly twice as large as the uncertainty in the monthly averages in the TOMS AI or AVHRR. *Cakmur et al.* [2001] point out that the data will be more robust to analyze mineral aerosols close to the source areas, where the errors are less important relative to the signal. Because TOMS AI, TOMS AOD, and AVHRR include all aerosols, not only mineral aerosols, we are required to be careful in evaluating our model results in regions not dominated by mineral aerosols. For the correlations shown below the satellite optical depths are interpolated onto the T62 grid (1.8° × 1.8° grid) used in the model before being correlated but after the monthly averages are calculated. During some months, there was insufficient data to interpolate onto the T62 grid at higher latitudes, and the AVHRR optical depths were interpolated only between 30°N and 10°S, causing spatial discontinuities in the correlation coefficients due to the change in the amount of data. Model optical depths are estimated from the four size bins following *Zender et al.* [2003].

[13] Comparisons between the seasonal mean optical depths from the model and AVHRR were shown to be good by *Luo et al.* [2003]. Figure 2 shows the correlation between the optical depth (at 380 nm for the TOMS comparisons and at 630 nm for the AVHRR comparison), in the model and observed TOMS AI (Figure 2a) and AVHRR (Figure 2e), and for the model versus the estimated TOMS AOD (Figure 2c). Over much of the high-desert-dust-loading region (0°–25°N in the tropical Atlantic) the model-TOMS AI comparison suggests high correlations (>0.8), while the comparison with the AVHRR optical depths (called AVHRR below) or TOMS AOD show moderate correlations (0.6–0.8). It is not clear why the correlation with TOMS AI is so much higher than TOMS AOD. This could be due to the difference in the robust time period (TOMS AI is robust only for 1984–1990) or due to differences between what the AI and AOD represent. The TOMS AOD is a combination of model and data and does not use this model, so this could be the source of the discrepancy. Also, the TOMS AOD could be removing artifacts from the TOMS AI due to the altitude of the aerosols, which accidentally correlate with the modeled desert dust.

[14] When we remove the seasonal cycle, and look at the model's ability to predict interannual variability (i.e., we remove the climatological mean monthly averages and compare monthly anomalies), we find that the correlations are much smaller, closer to 0.4, with the TOMS AI (Figure 2b), while they do not decrease as much (0.4–0.6) with the TOMS AOD (Figure 2d) or AVHRR (Figure 2f) in areas where the desert dust should be the dominant aerosol. *Cakmur et al.* [2001] analyzed TOMS AI and AVHRR and noted that the temporal correlation in the high-dust region between these two satellites was 0.55 once the seasonal cycle was removed. Thus the model and TOMS AI, TOMS AOD, or AVHRR correlations (0.4–0.6) are similar to the TOMS AI and the AVHRR (0.55). Notice that there is a moderate correlation in the anomalous dust just south of western North Africa (0°N and 0°E) in both the TOMS and the AVHRR comparisons. These areas are not likely to be dominated by desert dust but have significant contribution from biomass burning. The correlation between modeled desert dust and observed biomass burning might be explained by assuming that both are higher during drier years and highlights the need for critically evaluating the calculated correlation values before interpreting them. Rank correlation coefficients of both monthly mean and monthly anomalies are similar in spatial distribution but tend to be slightly higher (not shown).

[15] The fluctuations in TOMS AI between different years can be due to differences in aerosol height as well as optical depth. If the events tend to occur at approximately the same altitude each year, then the comparison between monthly anomalies in column amount and TOMS AI may be comparing similar properties (optical depth), and this assumption has been used and justified by *Hsu et al.* [1999] and *Cakmur et al.* [2001]. The similar correlations between the monthly anomalies using TOMS AI and TOMS AOD (Figures 2b and 2d) suggest that this assumption is largely valid. Overall, the model seems to have some skill in simulating interannual variability of desert dust close to the North African desert dust source, since the TOMS AI, TOMS AOD, and AVHRR comparisons suggest correlations above 0.6. The skill close to the Arabian Sea source is lower (0.4–0.6 in the TOMS AI and 0.2–0.4 in the TOMS AOD or AVHRR comparisons), while the skill close to the Asian source is even lower. Discrepancies between the model and observations may be related to interferences with other aerosols or failures in the model. The skill is also low near the Australian source, which may be due either to that source's relatively small magnitude or to failures in the model.

### 3.2. Variability in Model and Observations

[16] Next we look at the magnitude of the variability in the observations and how well the model is able to capture that variability. We define variability as the standard deviation divided by the mean and look at variability at in situ stations as well as satellites compared to the model results in this section. In Table 2 we show the variability within a month (intramonthly variability) and the variability between different years in the monthly mean (intermonthly variability). The standard deviations are calculated for every month and represent either the within month standard deviation (i.e., standard deviation of the daily averaged values within 1 month) or the between month standard deviation (e.g., July of 1983 versus July of 1984, etc.) and then are averaged to obtain a yearly value, which is then divided by the annual mean concentration. The variabilities are shown in Table 2 for both the model and observations at the 10 observing stations. Notice that for many of the observing stations, there are only weekly data available, in which case the weekly averages from the model are also

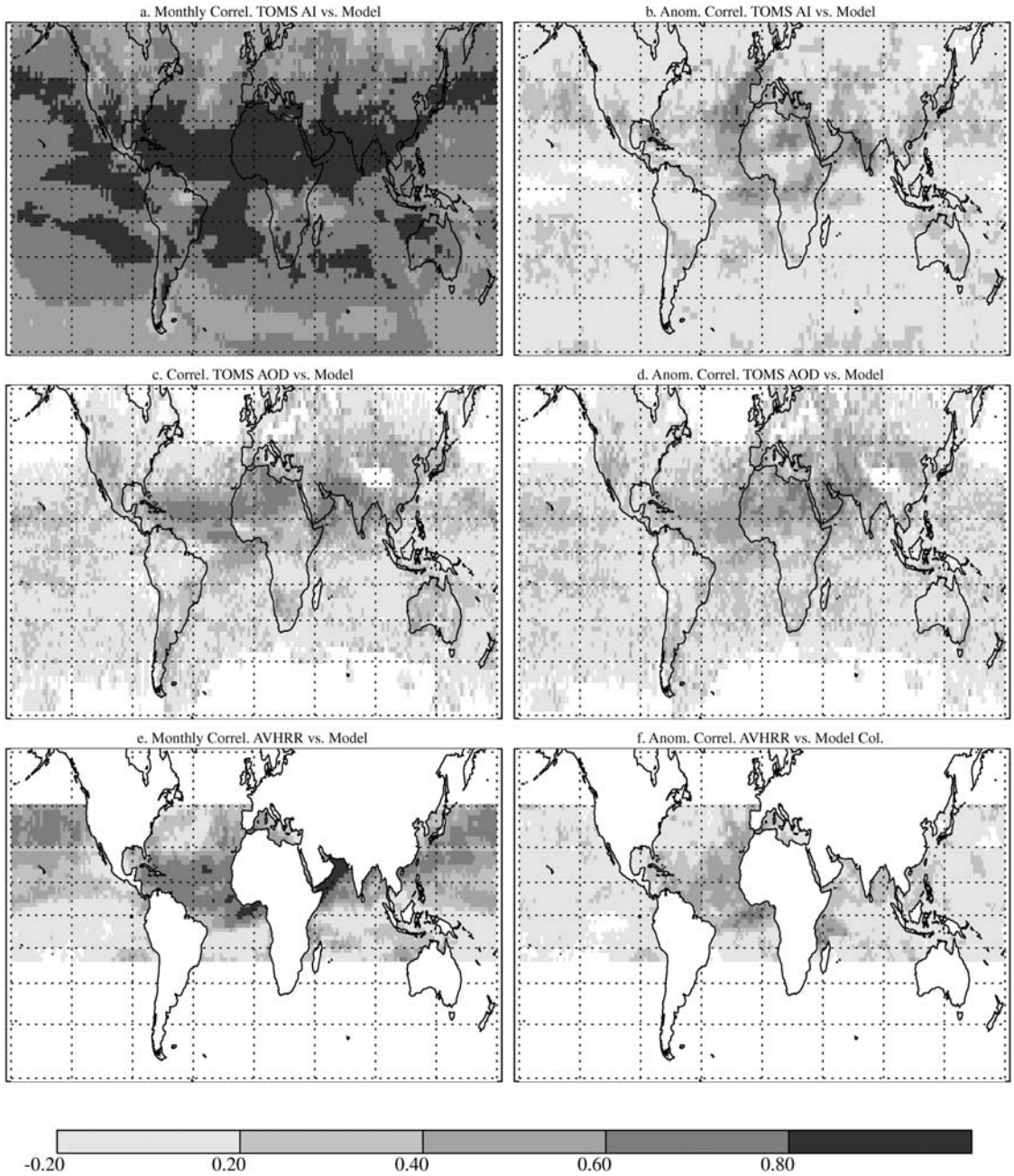



**Figure 2.** (a) Correlation between monthly mean Total Ozone Mapping Spectrometer (TOMS) Absorbing Aerosol Index (AI) [*Torres et al.*, 1998] and model aerosol optical depth (380 nm) for 1984–1990. (b) Correlation between monthly anomalies in TOMS AI and model optical depth (380 nm). (c) Model optical depth (380 nm) and TOMS AOD for 1983–1993 and 1996–2000 [*Torres et al.*, 2002]. (d) Correlation between monthly anomalies in TOMS AOD and model optical depth. (e) Correlation between advanced very high resolution radiometer (AVHRR) monthly mean optical depths [*Husar et al.*, 1997] and model optical depth (630 nm) for 1983, 1985–1990, and 1995–1998 (due to constraints on data availability and avoidance of volcanoes). (f) Correlations between anomalies in AVHRR and model optical depths.

used for comparison. As can be seen in Table 2, there is often 50% more variability inside of a month than between months in both the model and observations. This is presumably due to the highly event-based nature of desert dust transport. The model estimates intermonthly and intramonthly variability that is roughly similar to the observations at the observing stations, although the model seems to underestimate variability by ~25%. Because the model is considering the concentration averaged over a grid box, while the observations are looking at variability at one point, a higher variability in observations should be expected. However, we cannot eliminate the possibility that

**Table 2.** Intramonthly and Intermonthly Variability[a]

| | Intramonthly Standard Deviation/Mean Observation | Intramonthly Standard Deviation/Mean Model | Intermonthly Standard Deviation/Mean Observation | Intermonthly Standard Deviation/Mean Model |
|---|---|---|---|---|
| Barbados | 1.09 | .73 | 0.67 | 0.62 |
| Izana | 1.48 | 0.60 | 1.01 | 0.44 |
| Bermuda | 1.09 | 0.91 | 0.74 | 0.55 |
| Miami | 1.11 | 0.62 | 0.90 | 0.46 |
| Midway[b] | 0.73 | 0.81 | 0.58 | 0.48 |
| Hawaii[b] | 0.57 | 0.74 | 0.57 | 0.45 |
| Enewtak[b] | 0.76 | 0.67 | N/A | 0.44 |
| Funafuti[b] | 1.20 | 0.54 | 0.73 | 0.49 |
| Mace Head[b] | 1.34 | 0.65 | 0.78 | 0.46 |
| Norfolk[b] | 0.78 | 1.35 | 0.88 | 0.79 |

[a]Averaged over all months.
[b]Station only has weekly averaged data, so the model and observational calculations are based on weekly averages.

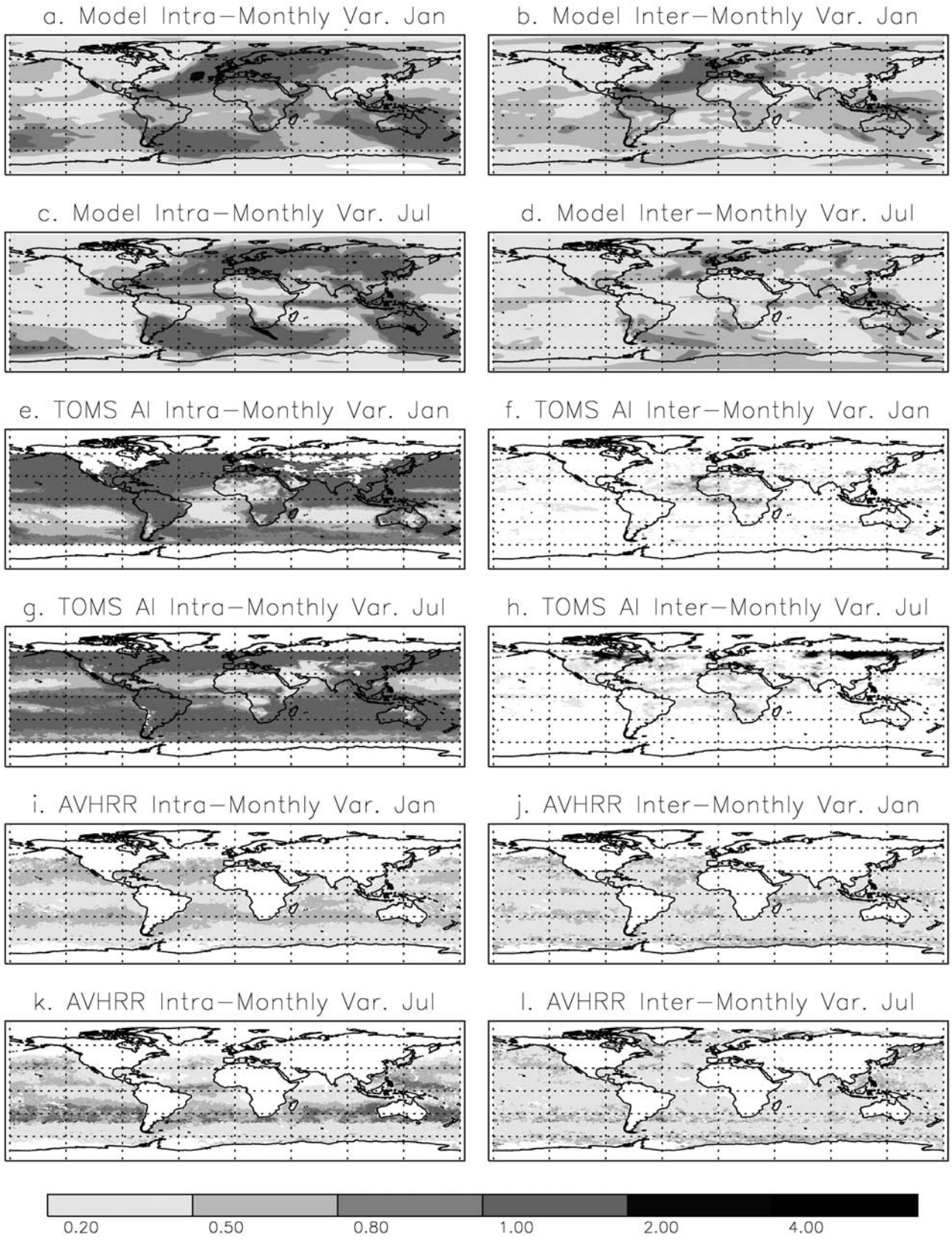
the model is underestimating variability in surface concentrations at the stations.

[17] Next we evaluate the model intramonthly and intermonthly variability (standard deviation/mean) in column amount by comparing to satellite retrievals. Because of the uncertainties in comparing satellite retrievals to models discussed above, the comparison between satellite and model variability in optical depth may be ambiguous in some locations. Figure 3 shows the intramonthly and intermonthly variability for January, and July, for the model column amount, the TOMS AI (calculated on the TOMS AI grid ($1^\circ \times 1.25^\circ$), and the AVHRR optical depths (on the AVHRR grid ($1^\circ \times 1^\circ$)). Because standard deviations within months are not available for the TOMS AOD, we do not include an analysis of TOMS AOD variability. In order to simplify our comparisons, we use column amount here. The correlations shown in Figure 2 are similar if done between observations and column amount and (in Figure 3) the variability in column amount and optical depths is similar. Overall, both model and observations suggest model intramonthly variability is larger than intermonthly variability (similar to that seen at the observing stations). Variability also tends to be larger outside of the strongest dust region between 0° and 20°N across North Africa and the tropical Atlantic in both the model and the observations.

[18] However, there is a large discrepancy between the variability seen in the TOMS AI and in the AVHRR optical depths for both the intramonthly and intermonthly variability. The TOMS AI has much more intramonthly variability than the AVHRR optical depths (with the model lying between these extremes), while the AVHRR optical depths has more intermonthly variability than the TOMS AI. These discrepancies could be due to sampling issues: For example, the TOMS AI is only used for 7 years, while the AVHRR is being considered for 13 years. Also, the AVHRR tends to include fewer data in the monthly mean than the TOMS, as discussed in section 3.1. In addition, the TOMS AI is dependent on aerosol height, so if our assumption that aerosol heights are roughly constant between years is incorrect, that would allow more variability in the TOMS AI than in the AVHRR optical depth. In addition, within monthly variability in the TOMS AI will include aerosol height variability as well as changes in the scan angle that may increase the intermonthly variability. There are reasons that the satellite data may represent different variability than the model. The TOMS AI or AVHRR optical depth is a snapshot at a given time, and at a finer horizontal resolution, than the model daily averaged values, which implies that diagnosed model variability would be higher if model data were subsampled at the frequency of satellite overpasses. To test the importance of horizontal resolution on variability, we interpolated the daily TOMS AI onto a T62 grid and calculated the standard deviation; this standard deviation tended to be less than the standard deviation calculated on the original TOMS grid, implying that a higher horizontal resolution will increase variability. There are also reasons why the TOMS AI and AVHRR optical depths should have a lower variability then the model. For example, satellite retrievals (TOMS AI or AVHRR optical depths) mean value include more aerosols than just mineral aerosols and have a detection limit (not reporting values lower than this limit). The combination of the above produces monthly mean TOMS AI or AVHRR, even in regions with minimal aerosols, of a minimum of $\sim$0.02 and $\sim$0.05, respectively, whereas the model predicts optical depths several orders of magnitude smaller [e.g., see *Luo et al.*, 2003, Figures 1 and 2]. This produces smaller variability in the satellite data than in the model in the same regions.

[19] The model values of intramonthly variability lie between TOMS AI and AVHRR optical depth estimates. For the intermonthly variability both the TOMS AI and AVHRR show less variability than the model simulation. This could be due to the larger mean optical depth discussed above or due to the model overestimating variability. Since the surface concentration data tended to suggest that the model was underestimating intermonthly variability, it seems likely that the discrepancy in the intermonthly variability may be due to the larger mean optical depths retrieved from satellites (from other aerosols and a higher detection limit) than predicted by the model.

[20] The spatial structure of the intra and intermonthly variability is similar; the largest values are observed just northwest of North Africa, especially during winter. Presumably, this means that every once in a while there is an event that transports dust into this region, while in the high-dust areas, there are regular events. Generally speaking, there is more variability in the less heavily impacted regions, right on the edge of the largest dust regions, similar to the intramonthly variability. Overall, it is difficult to evaluate the model variability from the satellites, but some of the same spatial and temporal structure is seen in the model and observations.


a. Model Intra−Monthly Var. Jan
b. Model Inter−Monthly Var. Jan
c. Model Intra−Monthly Var. Jul
d. Model Inter−Monthly Var. Jul
e. TOMS AI Intra−Monthly Var. Jan
f. TOMS AI Inter−Monthly Var. Jan
g. TOMS AI Intra−Monthly Var. Jul
h. TOMS AI Inter−Monthly Var. Jul
i. AVHRR Intra−Monthly Var. Jan
j. AVHRR Inter−Monthly Var. Jan
k. AVHRR Intra−Monthly Var. Jul
l. AVHRR Inter−Monthly Var. Jul
0.20
0.50
0.80
1.00
2.00
4.00

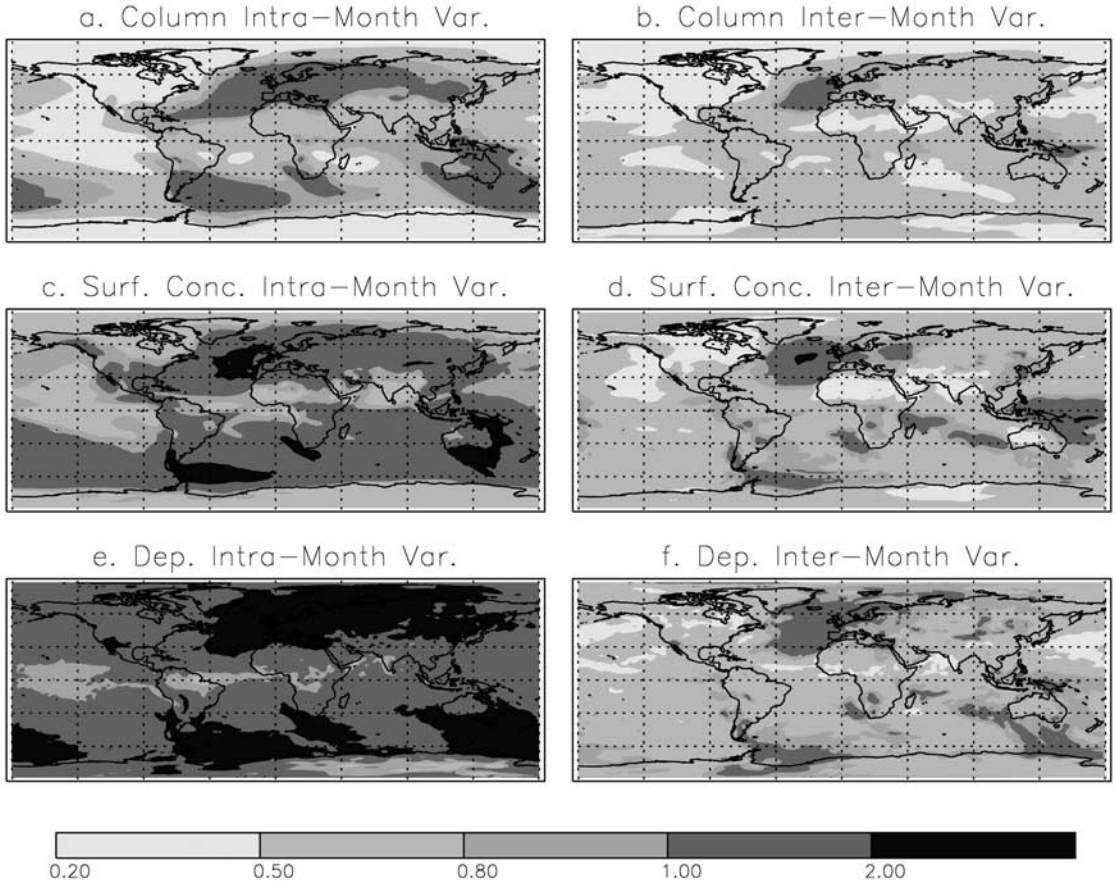



**Figure 4.** Annual average of the model variability in (a) intramonthly column, (b) intermonthly column, (c) intramonthly surface concentration, (d) intermonthly surface concentration, (e) intramonthly deposition, and (f) intermonthly deposition.

[21] There is some indication that model variability and skill (in terms of correlation with observations) are related. Increased variability means that there is a larger signal relative to the noise in interannual variability. If one looks at both the intermonthly variability (Figure 3) and the correlations between anomalies in dust column and TOMS AI (similar to Figure 2), one notices that both have their largest values in the same region northwest of North Africa. If we choose 18 points in the North Atlantic, in the region where most of the aerosols are mineral aerosols, spanning variability between 0.6 and 2.0 (from Figure 3) and correlations between the model and TOMS of 0.2 to 0.6 (from Figure 2) and correlate variability with model-TOMS AI correlation, we obtain a moderate correlation of 0.5. Similarly, using the station concentration data (section 3.1), if we compare correlation the model's variability within a month, and the model-observational daily correlation, we obtain a correlation of 0.4. If we look at intermonthly variability and the anomaly correlation between model and in situ observations, we obtain only a 0.l correlation, which does not support our view that increasing variability is correlated with increasing skill in the model.

[22] Figure 4 shows the intramonth and intermonth variability in an annual average for the column amount, the surface concentrations, and the deposition. Notice that generally the column amount has less variability than the surface concentration or the deposition, which is consistent with that variable being an integrated quantity (over the column). The deposition tends to have the most variability within the model, which is presumably due to the episodic nature of the wet deposition.

### 3.3. Climate Indices and Surface Concentrations at the Stations

[23] There are several climate indices that are hypothesized to be important in indicating interannual variability in

**Figure 3.** (opposite) Variability (standard deviation over mean) in the model and observations of column amount for (a) model intramonthly (within month) variability in January, (b) model intermonthly (between month) variability in January, (c) model intramonthly variability in July, (d) model intermonthly variability in July, (e) TOMS AI intramonthly variability in January, (f) TOMS AI intermonthly variability in January, (g) TOMS AI intramonthly variability in July, (h) TOMS AI intermonthly variability in July, (i) AVHRR optical depth intramonthly variability in July, (j) AVHRR optical depth intermonthly variability in July, (k) AVHRR optical depth intramonthly variability in July, and (l) AVHRR optical depth intermonnthly variability in July.

**Table 3.** Annual Average Concentrations Versus Climate Indices in Observations and Model[a]

| | NAO | PDO | Niño 3.4 |
|---|---|---|---|
| Barbados | 0.16 (**0.40**) | **0.36** (0.28) | 0.29 (0.12) |
| Izana | 0.26 (**0.42**) | 0.24 (**−0.40**) | −0.49 (−0.24) |
| Bermuda | 0.18 (−0.08) | 0.37 (0.18) | −0.18 (−0.20) |
| Miami | −0.21 (0.18) | 0.14 (0.15) | −0.24 (0.25) |
| Midway | −0.35 (−0.09) | 0.14 (**0.36**) | **−0.57** (**0.48**) |
| Hawaii | 0.32 (0.12) | **0.63** (**0.40**) | −0.20 (0.27) |
| Enewtak | **0.97** (0.18) | **0.63** (**0.43**) | 0.36 (**0.44**) |
| Funafuti | **0.88** (0.12) | 0.54 (−0.12) | 0.42 (0.22) |
| Mace Head | −0.45 (**0.60**) | −0.26 (−0.05) | **0.72** (−0.08) |
| Norfolk | **−0.71** (0.25) | 0.21 (−0.05) | −0.42 (0.00) |

[a]Model values are in parentheses, and statistically significant values are boldfaced.

weather, and here we look at comparisons between the in situ station data and climate indices. (In section 3.4 we look more broadly at spatial correlations between the climate indices and dust in the model.) The most famous is the El Niño/Southern Oscillation, which is a 2–3 year timescale oscillation that is very important for tropical Pacific weather and has teleconnections throughout the globe [e.g., *Trenberth*, 1996]. The North Atlantic Oscillation (NAO) has been shown to be important for the North Atlantic region, extending globally, and tends to change sign on decadal timescales [e.g., *Trenberth*, 1996]. The Pacific Decadal Oscillation (PDO) is seen in the North Pacific, and is also an oscillation seen on a decadal timescale [e.g., *Zhang et al.*, 1997; *Mantau et al.*, 1997].

[24] *Moulin et al.* [1997] reported that there are correlations of 0.66 and 0.49 between the NAO and Meteosat retrievals of aerosol optical depth between 1983 and 1994 for the Mediterranean and Atlantic regions, respectively, and a correlation of 0.50 between the Barbados in situ data and the NAO between 1965 and 1995. We explore here the relationship between the different station data and the climate indices in the observations and in the model. We start first by looking at the winter NAO (available at http://www.cgd.ucar.edu/(jhurrell/nao.html) [*Hurrell*, 1995], the Pacific Decadal Oscillation (available at ftp://ftp.atmos.washington.edu/mantua/pnw_impacts/INDICES/PDO.latest) [*Zhang et al.*, 1997; *Mantau et al.*, 1997], and El Niño 3.4 indices [available at ftp://ftp.ncep.noaa.gov/pub/cpc/wd52dg/data/indices/sstoi.indices) [*Trenberth*, 1996] and correlating these indices with the observations and model for the period 1979–2000 (Table 3). For this study we use annual average values for both the climate indices and the dust concentrations. For simplicity we assume that the annual average distributions meet the criteria such that we can discuss the statistical significance. The annual average of data is more similar to a Gaussian distribution than the monthly average data, but the required criteria are not actually met in either the data or the model concentrations. We also assume that individual annual averages are independent of each other, which is not the case if El Niño or NAO are important processes for dust, since they have longer than 1-year timescales. Thus the statistical significance of these correlations needs to be carefully interpreted.

[25] In contrast to the *Moulin et al.* [1997] study looking at 1965 to 1996, we do not obtain a statistically significant correlation between the NAO and the Barbados surface concentrations for the period 1979–2000 in the observations, only in the model. If we include the observations back to 1965, we obtain a correlation of 0.38, more similar to that calculated by *Moulin et al.* [1997]. This argues that some influences of the climate indices on atmospheric dust distributions will not be apparent over only a 22-year simulation, especially when we consider decadal timescales of variability such as the NAO. In fact, a correlation of 0.4 suggests that only 16% of the variability in the station data at Barbados is controlled by the NAO (even if we assume that the annual average concentrations at Barbados have a Gaussian distribution, which is untrue). Overall, the NAO is related to the observations at Enewtak and Funafuti only for the observations, but for Barbados, Izana, and Mace Head in the model. These results highlight the difficulty in interpreting correlations between dust concentrations and climate variables; there may be spurious correlations, such as between Enewtak and Funafuti and the NAO.

[26] We also conduct correlation analysis for other climate indices, such as the PDO and Niño 3.4 index for El Niño (there are many indices for El Niño, as discussed below) and show the results in Table 3. There are some correlations that do not appear to be physically significant (such as the correlation between Barbados and the PDO), but the correlation between Hawaii, Midway, and Enewtak and the PDO would appear reasonable owing to physical proximity. Notice the low correlations between the dust concentrations at the observing stations and the El Niño index. Since the El Niño index is well correlated with the first-mode variability in Empirical Orthogonal Function (EOF) analyses of precipitation [e.g., *Dai and Wigley*, 2000], it is interesting that it does not appear to correlate with atmospheric desert dust well, either in the model or observations at most stations; only at Midway does it correlate with both. This appears to be due to the location of the observing sites, according to the results in the next section. Notice that the observations suggest a negative correlation between Midway concentrations and the Niño 3.4 index, while the model suggests a positive correlation. This may be due to the shortness of the observed record or to errors in transport at Midway. As discussed below, the pattern of Niño 3.4 index correlation with the Pacific dust loading is rather complicated, so there may be a shift in the transport or precipitation patterns in the Pacific in the NCEP reanalysis from the real atmosphere. Note that if instead of using the PDO we use the North Pacific Index [*Trenberth and Hurrell*, 1994], we obtain similar results (not shown). Similarly, if we use another El Niño index (such as the Niño 3 index), we also obtain somewhat similar results to the Niño 3.4 index. We show only one index for simplicity of presentation.

[27] We also conducted correlation studies between the monthly anomalies of concentrations and the climate indices, instead of just annual average, as above. Unfortunately, these results do not show a clear picture of how climate indices might correlate with desert dust, so we do not show the results of these studies. We additionally did some analysis of lag correlations with monthly averages and again found few easily interpretable results, so we do not include them here.

### 3.4. Climate Index Correlations With Model Results

[28] We expand the above analysis to look at where the variability in modeled dust appears to be related to the

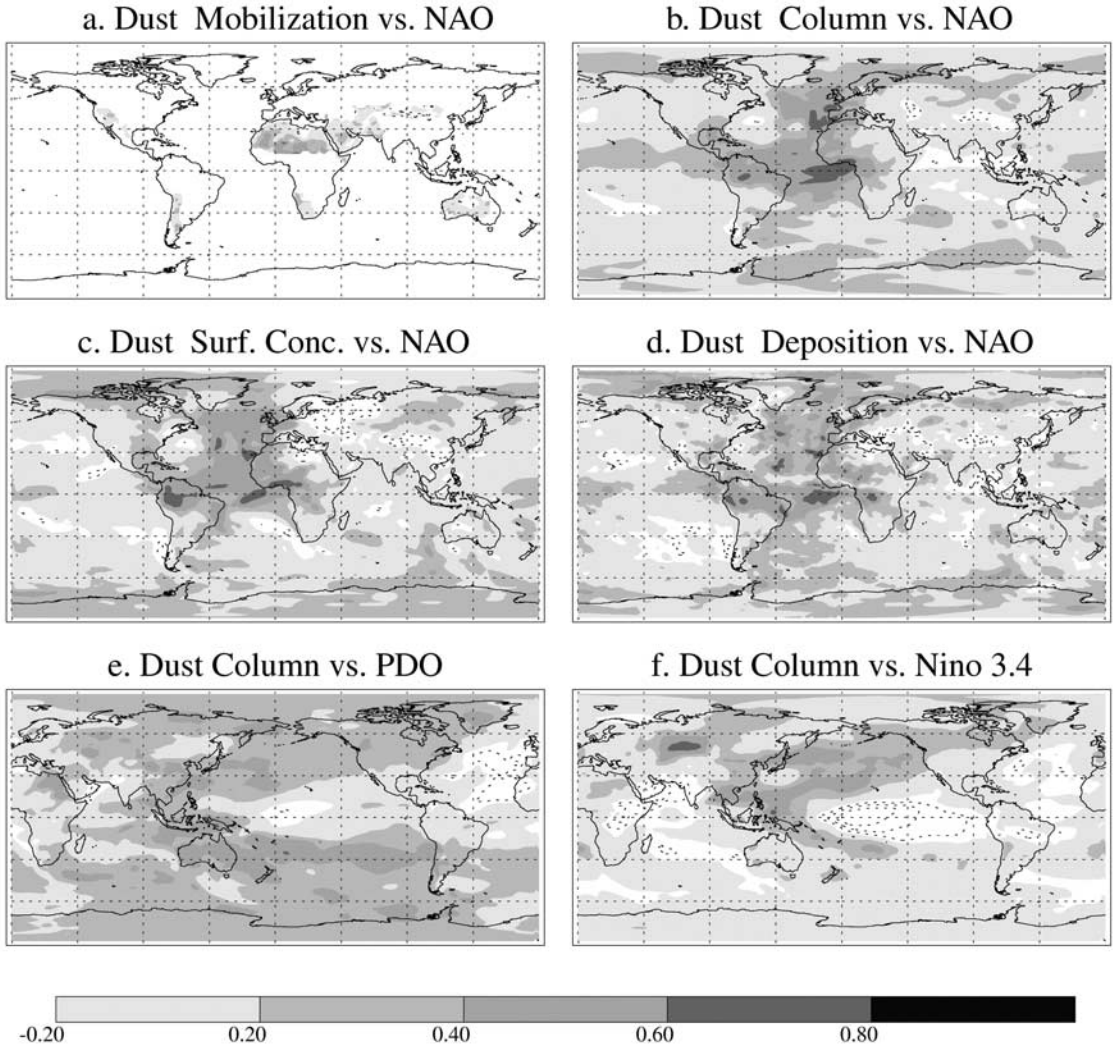



**Figure 5.** Correlation between the wintertime (a) North Atlantic Oscillation and annual average model mobilization, (b) column amount, (c) surface concentration, and (d) deposition. Correlation between (e) annual average dust column amount and Pacific Decadal Oscillation and (f) El Niño index 3.4.

climate indices. Figure 5 shows the correlation between the NAO and the annual average mobilization (Figure 5a), dust column (Figure 5b), surface concentration (Figure 5c), and deposition (Figure 5d). Mobilization in North Africa is correlated at the 0.6 level at some locations in North Africa with the NAO. Concentrations and column depth in the eastern and southern parts of the North Atlantic are correlated at the 0.4 level, while deposition throughout the North Atlantic basin is correlated at the 0.2–0.6 level with the wintertime NAO. The spatial structure of these correlations is consistent with the strong correlation in the Mediterranean and eastern North Atlantic seen in the Meteosat aerosol optical depths [*Moulin et al.*, 1997].

[29] Figures 5e and 5f show the correlation between modeled column amount and the PDO and Niño 3.4 indices. In the both the North and South Pacific the PDO show moderate correlations (0.4–0.8) with the distributions. If we contrast this with correlations with the North Pacific Index (not shown), the North Pacific Index shows a stronger positive correlation farther north in the Pacific than the PDO. The Niño 3.4 index is correlated with high-dust column amount in the western part of the tropical Pacific and lower dust in the eastern tropical Pacific, consistent with precipitation pattern shifts due to El Niño [e.g., *Dai and Wigley*, 2000]. A reason that the El Niño signal does appear very strong in the Hawaii and Funafuti station data may be the location of the stations; they appear to be where the correlation changes sign. Notice that the Midway correlations in Table 3 are actually opposite in sign between the observations and the model. This may be due to a shift precipitation between the NCEP reanalyses and the atmosphere.

[30] Unfortunately, it is difficult to verify these comparisons with the available satellite data. We have 13 years of data from the AVHRR while TOMS AI is only robust for ~8 years, not long enough to capture decadal variability such as that described by the NAO or PDO or even El Niño. In addition, these satellite retrievals represent mineral aerosol only in a small area of the globe. Results of this analysis show that the satellites are positively correlated in the North Atlantic region (0°–20°N) with the NAO in either the AVHRR or the TOMS AI (not shown). The TOMS AI or

**Table 4.** Station to Station Monthly Anomaly Correlations: Observations and Model[a]

| Stations | Barbados | Izana | Bermuda | Miami | Midway | Hawaii | Enewtak | Funafuti | Mace Head |
|---|---|---|---|---|---|---|---|---|---|
| Izana | 0.01 (**0.28**) | | | | | | | | |
| Bermuda | 0.09 (0.07) | 0.02 (0.09) | | | | | | | |
| Miami | **0.18** (**0.21**) | −0.03 (0.08) | **0.51**(**0.57**) | | | | | | |
| Midway | −.03 (−**0.11**) | 0.25 (−**0.15**) | 0.12 (0.00) | 0.09 (0.06) | | | | | |
| Hawaii | 0.01 (−**0.16**) | 0.67 (−**0.14**) | −0.59 (0.02) | 0.03 (0.01) | **0.25** (**0.57**) | | | | |
| Enewtak | 0.09 (−0.04) | 0.00 (0.00) | 0.00 (0.00) | −0.26 (0.00) | −0.27 (**0.37**) | −0.04 (**0.42**) | | | |
| Funafuti | 0.19 (0.07) | 0.00 (0.00) | 0.00 (0.00) | −0.15 (0.00) | 0.11 (−0.04) | 0.01 (−0.04) | −0.09 (−0.06) | | |
| Mace Head | 0.11 (0.09) | 0.03 (**0.39**) | −0.08 (0.01) | −0.14 (0.02) | 0.00 (−0.09) | −0.26 (−0.05) | 0.00 (0.00) | | |
| Norfolk | −0.12 (0.10) | **0.92** (0.04) | −**1.00** (−0.01) | 0.19 (0.05) | 0.06 (−0.00) | −0.02 (0.01) | 0.11 (0.03) | −0.43 (0.05) | −0.88 (0.00) |

[a]Model values are in parenthesis. Statistically significant results are boldfaced (assuming the distributions are Gaussian).

AVHRR correlations with Niño 3.4 show a weak maximum over the Indonesia region (not shown), consistent with the model. The TOMS AI and AVHRR optical depths did not show a consistent correlation with PDO, and the TOMS AOD show little correlation with any of the indices. Overall, the model correlations with the climate indices appear roughly consistent with observations, but a 22-year simulation is too short a time period to do robust correlations with decadal oscillations such as the NAO or PDO, so these results should be regarded with caution.

### 3.5. Station to Stations Correlations

[31] Another way to evaluate the model is to look at the relationships in concentrations between stations seen in the observations and evaluate whether they are captured in the model. For example, if fluctuations in the magnitude of the mobilization in North Africa are responsible for fluctuations at the North Atlantic, we would expect the stations downwind of North Africa (Barbados, Bermuda, Miami, and Izana) to be correlated, and we would hope the model would be able to capture these fluctuations. (In section 3.6 we look more broadly at the spatial correlations within the model and the representativeness of the station data for nearby regions.) We evaluate this using the monthly mean anomalies from the model and observations and correlate these for the different stations, as shown in Table 4.

[32] There are moderate correlations (0.5–0.7) between monthly anomalies in the observations seen between Hawaii and Izana and between Miami and Bermuda, and there is even a strong correlation between Norfolk and Izana. It is unclear why Hawaii and Izana or Norfolk and Izana would be correlated, and this is not captured in the model; it is likely that this type of spurious correlation is due to the small time series we are correlating or the fact that we are using correlations in the case of non-Gaussian distributions. However, the physically justifiable correlations between Miami and Bermuda or Miami and Barbados are captured by the model. Mace Head and Izana are correlated in the model but not in the observations. This could be due to the elimination of data from easterly wind sectors (i.e., from Europe) done in the observations at Mace Head but not done in the model. The model also predicts a moderate correlation between concentrations at Midway and Hawaii, while the observations suggest only a low correlation, although both are statistically significant (if we incorrectly assumed that the model and observations of monthly mean concentrations were Gaussian distributed). The model predicts correlations between Enewtak and Hawaii, which are not seen in the observations. Surprisingly, there is little correlation between Barbados and Bermuda or Bermuda and Izana, including in the anomalous monthly comparison (which removes differences in the seasonal cycle), implying that the whole North Atlantic region is not equally dusty during different months. Overall, there are not strong correlations between the different stations, suggesting that much of the variability seen at the observing stations during 1979–2000 is not due to changes in large-scale sources magnitude but rather due to transport fluctuations or smaller-scale source fluctuations. The model and observations agree on this lack of strong correlations between stations.

### 3.6. Representativeness of the Observations

[33] Unfortunately, we are limited in our ability to make observations of mineral aerosols globally. This makes it important to understand the region over which the available observation stations represent the fluctuations in dust, or what we will define as the station's representativeness. In this analysis, we use the model to estimate how representative the different stations are of the region near them by correlating surface concentrations in the model at the different stations with nearby dust concentrations, column amounts, and deposition, also from the model. From section 3.5 we have some confidence in the ability of the model to predict the correct scales of variability, which tend to be smaller than the distance between most of the stations. Since mesoscale and subgrid-scale processes are included only in a very coarse manner in our model, this analysis is likely to overestimate the representativeness of the observing stations. In addition, the results of this study will be sensitive to the model we used. For example, this model simulates more wet deposition than dry deposition in regions remote from the sources. Since wet deposition requires not only dust concentrations but also precipitation, this will shift the patterns slightly from another model study more dependent on dry deposition. Of course, errors in the mean circulation or precipitation in the NCEP reanalyses will also cause errors in the patterns.

[34] Since Barbados has the longest record, we first consider that observation station and then more briefly the other stations. First, we show the correlations between modeled monthly averaged concentrations at the surface and modeled dust column amount (Figure 6a). Notice that because both North Africa and the Arabian Peninsula have more dust in the summer, these areas are correlated with the Barbados surface concentrations. The correlations seen close to Barbados of over 0.8 are consistent with in situ correlations between concentration and AERONET data

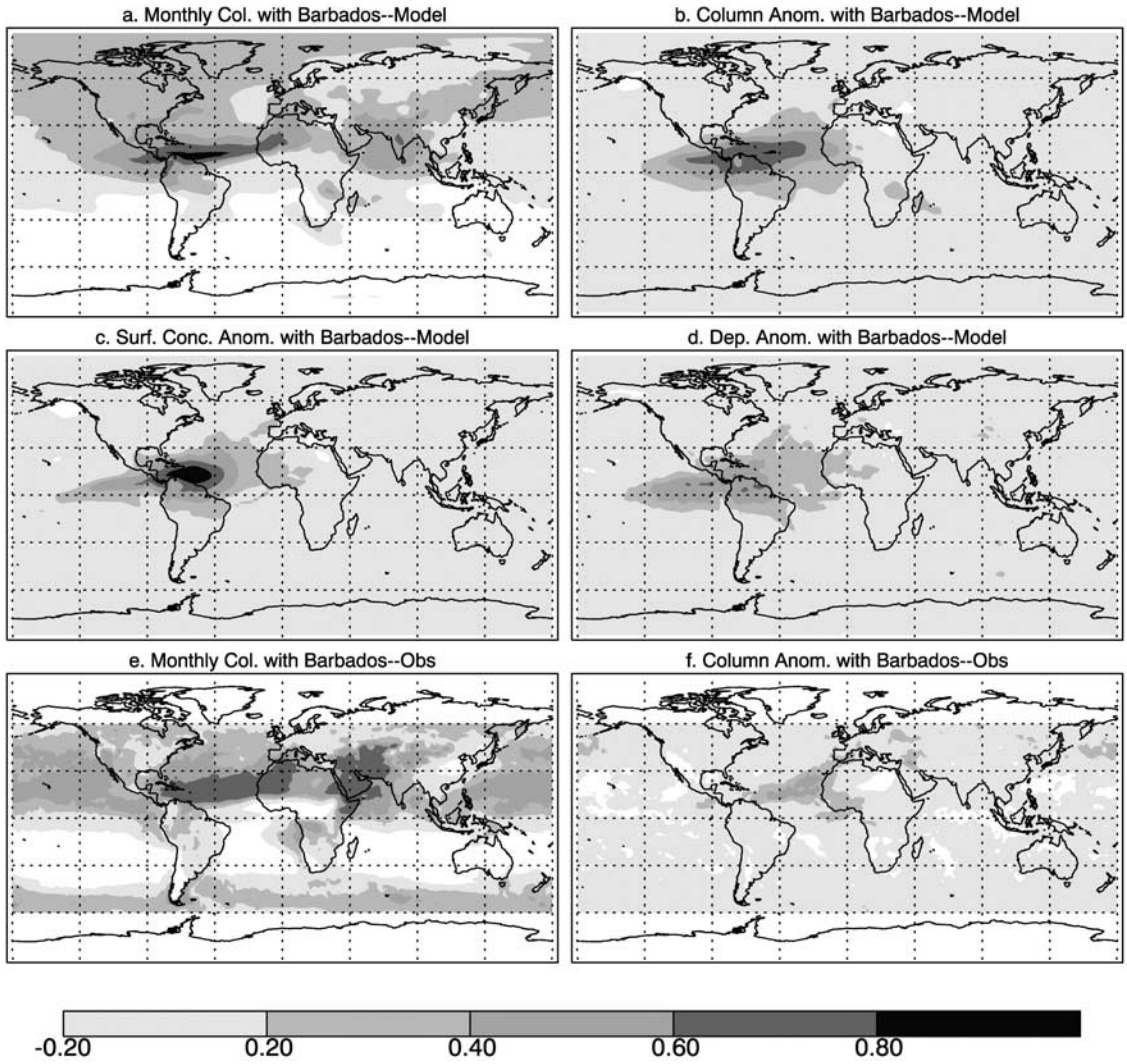



**Figure 6.** (a) Correlation between the modeled time series of surface concentration at the Barbados station and different grid boxes for modeled column amount to show the ''representativeness'' of the station. Figures 6b–6d show the correlation between the anomalous concentrations at Barbados and (b) the anomalous column amount, (c) surface concentration, and (d) deposition. (e) Monthly averaged TOMS AI correlation with the Barbados observations. (f) Correlations between the anomalies in the monthly mean TOMS AI and Barbados observations.

[*Smirnov et al.*, 2000]. A more insightful way to look at the data is to remove the monthly mean concentrations and view just the correlation between the monthly mean anomalies in column amount and concentration at the Barbados station (Figure 6b). Figure 6b represents more clearly the region where the variability at Barbados is similar within the model. There is a small correlation (0.2–0.3) between Barbados monthly average anomalies and mobilization in the western part of North Africa and near the Bodele basin (not shown). In the correlations with column amount, surface concentrations (Figure 6c), and deposition (Figure 6d), there is a moderate to high correlation between the surface concentration at Barbados, with a maximum correlation of above 0.8 over Barbados, extending throughout the Caribbean, as far west as the western Pacific, and as far east as North Africa. The correlations are strongest for the largest area between the monthly anomalies in surface concentrations at Barbados and the column amount. If we correlated instead annual averages, we would obtain roughly consistent results close to the observing stations but with more ''noise'' in regions far away from the observing station (not shown in figures). Notice that the correlations between the deposition near Barbados and the concentrations observed at Barbados are low (0.4–0.6) compared with the correlations between the concentration at Barbados and column amounts at Barbados (0.8–1.0). In this model, the interannual variability in deposition is difficult to observe for a region, probably at least partly due to the importance of wet deposition in this model.

[35] It is somewhat difficult to verify that the model results of representativeness are correct, because we are limited to satellite data for large-scale analysis. As discussed above, interpreting the satellite results is not always easy, and we can only compare with satellite observations in

regions where we expect the dominant aerosol to be mineral aerosol, which limits us to the North Atlantic south of ~25°N [e.g., *Cakmur et al.*, 2001]. Figure 6e shows the correlation between the Barbados observations and the TOMS AI for 1984–1990 using the monthly means and in Figure 6f using the monthly anomalies. The regions with a correlation tend to be similar to those in the model, although not as clearly defined. Considering the caveats in using the satellite data, these comparisons are encouraging enough that the model study of representativeness may be reasonable. We do not show results using the TOMS AOD or AVHRR satellite retrievals, but these are similar (but with more noise).

[36] Next we show results from more stations and the correlations between surface concentrations and the nearby grid points in our model for concentration and deposition, shown in Figure 7. The correlations between concentration and concentration at the observing stations are usually the highest (not shown in figures), with similarly high correlations between column amount and station surface concentration, while monthly anomaly deposition near the stations and surface concentrations at the station are usually low to moderately correlated.

[37] The Izana station appears to measure a different region than Barbados; the correlations are strongest extending to the north into Europe. The Bermuda station captures the region close to Bermuda, again not overlapping with the Barbados or Izana representative regions. The Miami station captures a region slightly overlapping both Barbados and Bermuda. The Mace Head station in Ireland is representative of the northern parts of the North Atlantic. The Midway, Oahu, and Enewtak stations are representative of regions in the Pacific that tend to be larger than the stations in the North Atlantic, perhaps because these stations are farther from the sources. The Funafuti station in the Southern Hemisphere has a very small region that is highly correlated, perhaps due to the high amounts of precipitation in this region. Norfolk, near Australia, also has a small area where it is highly correlated (but an area larger than the Funafuti station). The correlation between Norfolk Island and either the column amount or deposition extends over a larger area than the concentration correlations (not shown). In fact, there is some correlation in the deposition in the Southern Ocean and the station data at Norfolk. These results are consistent with the station to station correlations shown in Table 4. We do not attempt to verify these relationships in the observations because either stations do not have sufficient data or they are in regions where the mineral aerosols are not the dominant aerosols, and thus we do not expect the same relationships as seen in the dust model.

[38] Finally, we consider the representativeness of the satellite data. In the future we will have interannual variability in optical depth from many more satellites. We address the question here of how much information these aerosol retrievals provide about variability in surface concentrations and deposition, especially in terms of the monthly average and monthly anomaly values. In order to address this point, we look at the correlation in time at every grid point between the column amount and surface concentration or deposition at the same grid point. We assume here that we have observations at every grid point, as a perfect satellite would give us. Figure 8 shows the correlation between monthly average column amount and surface concentration (Figure 8a), between surface concentration and deposition (Figure 8c), between column amount and deposition (Figure 8e), and between column amount and mobilization (Figure 8g). The correlations can be quite high, above 0.8, but the correlations are actually negative in some locations, often associated with strong marine boundary layers close to shore (e.g., off the coast of North Africa in Figure 8a, where the midtropospheric level dust transport during the summer is referred to as the Saharan Air Layer) or with strong precipitation (at the equator in North Africa in Figure 8c). The correlations between the monthly anomalies have a similarly large range (Figures 8b, 8d, 8f and 8h). Correlations between column amount and mobilization over the source areas range between 0.2 and 0.8, suggesting that in many source regions, variability in the retrieved optical depths may not be able to indicate accurately variability in source strengths. Overall, the deposition is the least well correlated with column amount or surface concentration over regions far from the sources. Because our model may overestimate wet deposition, Figures 8e and 8f may underestimate the real "representativeness" of the satellite data. The correlation between dry deposition and column amount is similar to the correlation between surface concentration and column (Figures 8a and 8b).

[39] We can also correlate during each month the spatial distribution of the column amount predicted in the model and the surface concentration and deposition. This provides insight into how much information is provided by the monthly mean optical depths from the satellite about the spatial distributions of the monthly mean surface concentrations, deposition, and mobilization underneath the column amounts. We use column amount here as a proxy for optical depth, so we need not look at several optical depths. Column amount is related to optical depths, with size-dependent coefficients, so that as long as the size distributions are not changing very much with space or time (which is true for our model), using column amount gives a good proxy for optical depth. In the real world, size distributions may change more than in the model, implying that the relationship between optical depth and concentration or deposition may be less related than those inferred in the model. These correlations average to a correlation of 0.85 between surface concentration and column amount, 0.70 between deposition and column amount, 0.86 between surface concentration and deposition, and 0.56 between mobilization and column amount (only calculated over land). This implies that if one perfectly observed the monthly mean optical depth (and we have normally distributed errors) during a given month, one could predict 75% of the spatial variability in surface concentrations, 50% of the spatial distribution of the deposition fluxes, and only 25% of the spatial distribution of the mobilization. The deposition variability captured from satellite may be an underestimate if the model is overpredicting the relative amount of wet deposition; the value would be closer to 75% (similar to surface concentrations). This analysis suggests that satellite retrievals of aerosol optical depth may be difficult to extrapolate to monthly mean or interannual variability in deposition or

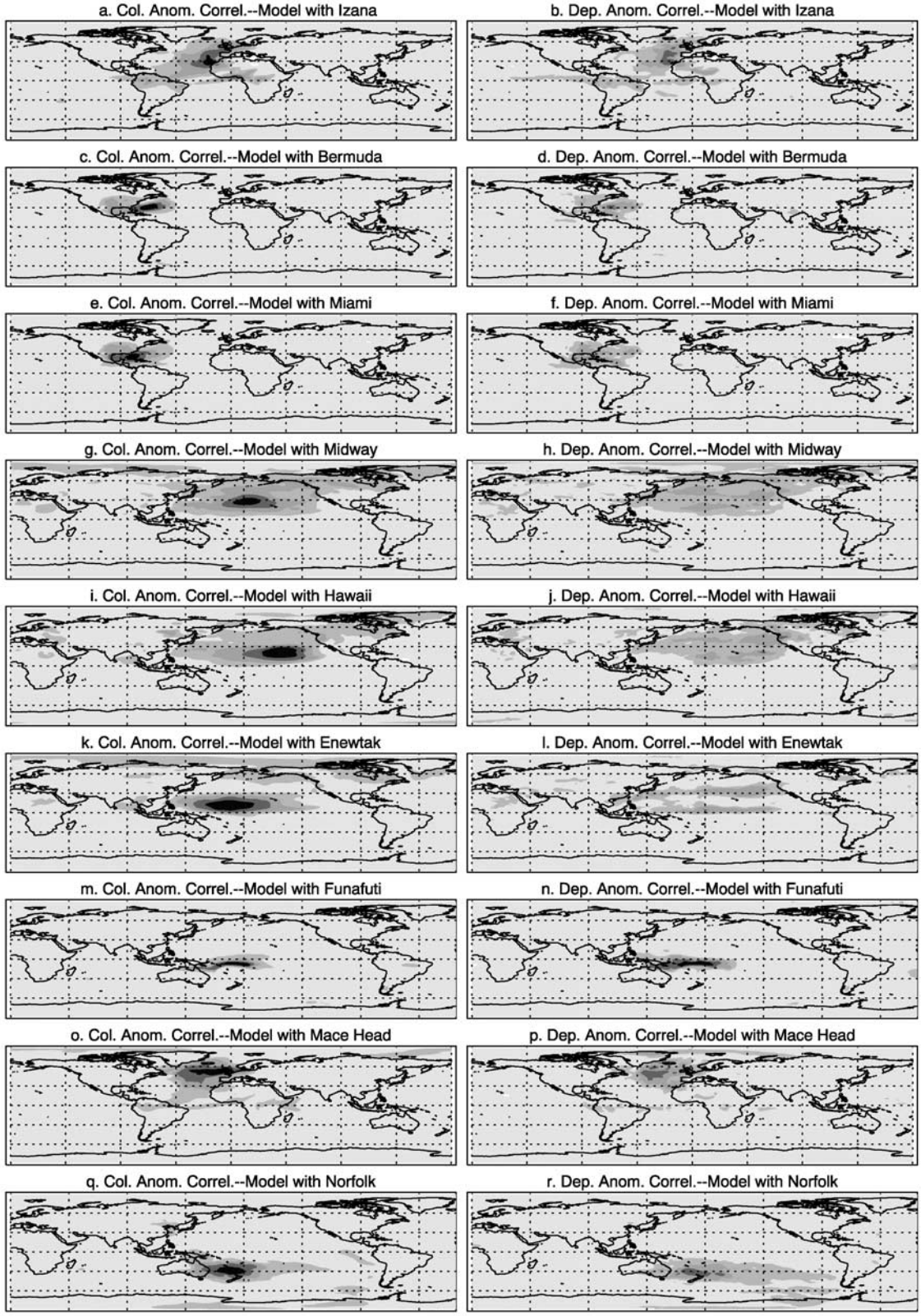



**Figure 7.** Correlation between the anomalous column amount (or deposition) and the station surface concentration in the model for (a and b) Izana, (c and d) Bermuda, (e and f) Miami, (g and h) Midway, (i and j) Hawaii, (k and l) Enewtak, (m and n) Funafuti, (o and p) Mace Head, and (q and r) Norfolk.

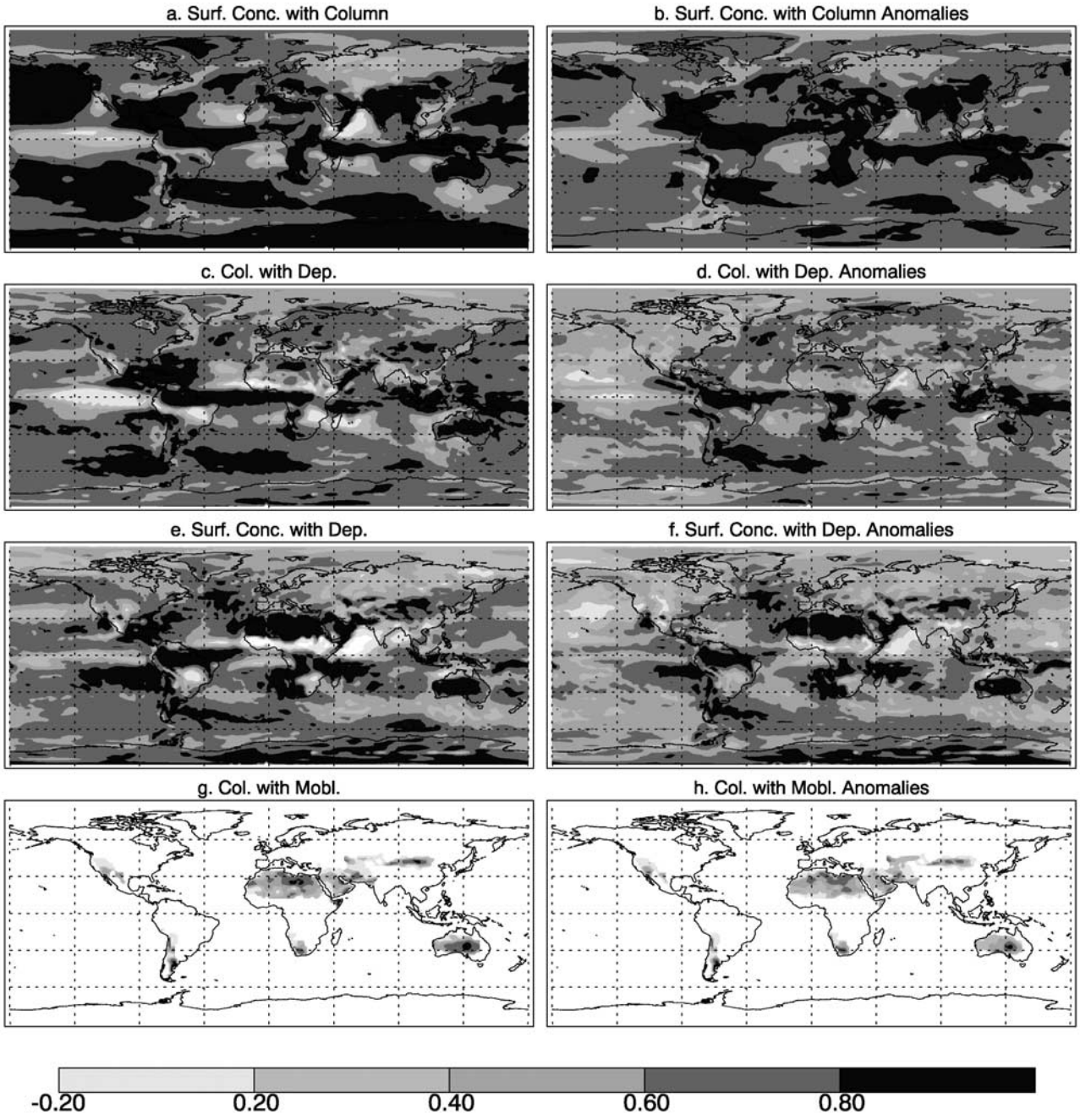



**Figure 8.** Correlation between the modeled values at the same grid points of (a) monthly mean surface concentration and column amount, (b) monthly anomalies in column amount and surface concentration, (c) monthly mean column amount and deposition, (d) monthly anomalies of column amount and deposition, (e) monthly mean surface concentration and deposition, (f) monthly anomalies in surface concentration and deposition, (g) monthly mean column amount and mobilization, and (h) monthly anomalies in column amount and mobilization.

mobilization but may provide more information about surface concentration variability.

### 3.7. Role of Source Variability

[40] *Tegen and Miller* [1998] show that in their GCM-based dust model, much of the variability in concentrations is controlled by transport fluctuations. They study transport variability using two sets of experiments: one in which the source is constant each year and one where the source is allowed to vary. We do not have available to us a constant source simulation; however, we look at the size of the variability in modeled concentration at four observing stations and sources and whether the variability in concentrations are correlated with variability in the source strength.

[41] Because the relationship between source strength and downwind concentrations is roughly linear, we can estimate the annual average concentration at a station (**c**, which is the vector containing annual averages from 1979 to 2000) as

**Table 5.** Transport Variability and Correlations in Model Simulations[a]

| Source Area | Variability in Concentration Var $(\mathbf{c})/(\bar{\mathbf{c}})^2$ | Variability in source $\mathrm{Var}(\mathbf{s_i})/(\bar{\mathbf{s}}_\mathbf{i})^2$ | Variability in Concentration From Source $(\bar{\mathbf{c}}_\mathbf{i}/\bar{\mathbf{c}})^2\mathrm{Var}(\mathbf{s_i})/(\bar{\mathbf{s}}_\mathbf{i})^2$ | Correlations Annual Mobilization Versus Concentration | Correlation Monthly Mobilization Versus Concentration | Correlation Monthly Anomaly Mobilization Versus Concentration |
|---|---|---|---|---|---|---|
| | | | *Barbados* | | | |
| West Africa | 0.047 | 0.018 | 0.0021 | 0.26 | 0.45 | 0.30 |
| Central Africa | | 0.022 | 0.0067 | −0.03 | 0.36 | 0.20 |
| West and Central Africa | | 0.016 | 0.0125 | 0.11 | 0.43 | 0.29 |
| | | | *Bermuda* | | | |
| West Africa | 0.086 | 0.018 | 0.0015 | 0.46 | 0.13 | 0.14 |
| Central Africa | | 0.022 | 0.0085 | 0.19 | −0.06 | 0.10 |
| West and Central Africa | | 0.016 | 0.013 | 0.35 | 0.02 | 0.13 |
| | | | *Hawaii* | | | |
| Asia | 0.044 | 0.038 | 0.00095 | 0.26 | 0.10 | 0.13 |
| Central Asia | | 0.021 | 0.00038 | −0.09 | −0.08 | 0.04 |
| West and Central Africa | | 0.016 | 0.0032 | 0.42 | 0.52 | 0.05 |
| | | | *Norfolk* | | | |
| Australia | 0.15 | 0.045 | 0.041 | 0.53 | 0.49 | 0.33 |

[a]Variability in this table is the square of variabilities in the previous tables. Variability represents annual values.

the sum of the contributions from each source, $\mathbf{c_i}$ (where $i$ indicates the source area), which is a function of a vector of source strengths $\mathbf{s_i}$ multiplied by a vector of the linear transport factor $\mathbf{t_i}$. Here we assume that transport is linear. In our model it will be close to linear, but in the real world, wet removal may occur nonlinearly if the dust aerosols are interacting with the precipitation

$$\mathbf{c} = \sum_i \mathbf{c_i} = \sum_i \mathbf{s_i t_i}. \tag{1}$$

We can rewrite $\mathbf{c_i}$, $\mathbf{s_i}$ and $\mathbf{t_i}$ as the sum of a mean over time (denoted by an overbar) and anomalies from the mean (denoted by a prime). If we assume that the anomalies from the mean are small compared to the mean, we obtain equation (2)

$$\frac{\mathbf{c_i'}}{\bar{\mathbf{c}}_\mathbf{i}} = \frac{\mathbf{s_i'}}{\bar{\mathbf{s}}_\mathbf{i}} + \frac{\mathbf{t_i'}}{\bar{\mathbf{t}}_\mathbf{i}}. \tag{2}$$

If we define the variance of vector $\mathbf{x_i}$ ($\mathrm{Var}(\mathbf{x_i})$) as the sum over $n$ time samples of $(\mathbf{xi}')^2/(n-1)$, and the covariance of $\mathbf{y_i}$ and $\mathbf{x_i}$ as the sum of $(\mathbf{x}'_\mathbf{i}\mathbf{y}'_\mathbf{i})/(n-1)$ over $n$ time samples, then we can obtain the following linearized equation for variance in concentration from each source (R. Miller, personal communication, 2002):

$$\frac{\mathrm{Var}(\mathbf{c_i'})}{(\bar{\mathbf{c}}_\mathbf{i})^2} = \frac{\mathrm{Var}(\mathbf{s_i'})}{(\bar{\mathbf{s}}_\mathbf{i})^2} + \frac{\mathrm{Var}(\mathbf{t_i'})}{(\bar{\mathbf{t}}_\mathbf{i})^2} + 2\frac{\mathrm{Covar}(\mathbf{s_i'}, \mathbf{t_i'})}{\bar{\mathbf{t}}_\mathbf{i}\bar{\mathbf{s}}_\mathbf{i}}. \tag{3}$$

The total variance in concentrations over the mean is then shown in equation (4)

$$\begin{aligned}\frac{\mathrm{Var}(\mathbf{c}')}{(\bar{\mathbf{c}})^2} &= \frac{\left(\sum_i \mathbf{c_i'}\right)^2/(n-1)}{(\bar{\mathbf{c}})^2} \\ &= \sum_i \frac{(\bar{\mathbf{c}}_\mathbf{i})^2}{(\bar{\mathbf{c}})^2}\left[\frac{\mathrm{Var}(\mathbf{s_i'})}{(\bar{\mathbf{s}}_\mathbf{i})^2} + \frac{\mathrm{Var}(\mathbf{t_i'})}{(\bar{\mathbf{t}}_\mathbf{i})^2} + \frac{\mathrm{Covar}(\mathbf{s_i'}, \mathbf{t_i'})}{\bar{\mathbf{t}}_\mathbf{i}\bar{\mathbf{s}}_\mathbf{i}}\right] \\ &\quad + \sum_i \sum_{j\neq i} \frac{\mathrm{Covar}\left(\mathbf{c_i'}, \mathbf{c_j'}\right)}{(\bar{\mathbf{c}})^2}.\end{aligned} \tag{4}$$

Thus the variability in concentration (in this section we define variability as the variance over mean squared, so roughly the square of sections 3.1–3.6) has contributions from source variability, transport variability in addition to the covariance of source and transport variability, and a covariance in the contributions from different sources.

[42] In this paper, we can only calculate the variability in the concentration (the left-hand side of equation (4)) and the variability in the sources (the first term on the right-hand side of equation (4)). We estimate the mean contribution from each source ($\mathbf{c_i}$) from a simulation by *Luo et al.* [2003], which included a source apportionment study using seven different source areas (West Africa, Central Africa, East Africa, Arabian Pennisula, East Asia, Australia, and all others). As seen in the work of *Mahowald et al.* [2002], slightly different source areas tend to give very similar concentrations at the downwind stations. Thus it is likely that the exact geometry of the sources is not important for downwind concentrations, which allows us to look at mobilization averaged over regions. The variability in transport from each source is unknown; we would need to conduct a 22-year simulation with each source area separately tagged.

[43] In Table 5 we look at the concentration variability (left-hand side of equation (4)), and the contribution of the source variability to this station (first term on the right-hand side of equation (4)) for the sources that are most important at four observing stations (Barbados, Bermuda, Mauna Loa, and Norfolk Island). The variances are calculated for the annual mean quantities; notice that the variability in Table 5 is the square of the variability in previous tables. In addition, temporal correlations between the area average source strength and the concentration for annual average, monthly average, and anomalous monthly averages are also shown in Table 5. For all four stations the variability in the source regions are smaller than the variability in surface concentration at the sources, especially when the contribution from that source area to the station is included in the calculation $(\bar{\mathbf{c}}_\mathbf{i}/\bar{\mathbf{c}})^2 var(\mathbf{s_i})/(\bar{\mathbf{s}}_\mathbf{i})^2$. The correlation between the annual average source strength and surface concentra-

tion is only correlated moderately well (0.3–0.5) in four cases (Bermuda versus West Africa, Bermuda versus West and Central Africa, Hawaii versus West and Central Africa, and Norfolk versus Australia), and no correlations above 0.35 are calculated when monthly anomalies are used instead. Thus at all four of these sites, transport variability and/or transport and source covariances are responsible for a large part of the observed fluctuations, consistent with *Tegen and Miller* [1998]. The importance of sources variability over the 1979–2000 period is very different than what may have been the case during longer time periods [e.g., *Mahowald et al.*, 1999, 2002], when changes in source strength and location are likely to have taken place.

## 4. Summary and Conclusions

[44] The interannual variability simulated in a 22-year dust modeling study is shown to be roughly consistent with available observations. Comparisons between model and observations at in situ sites of monthly average surface concentrations suggest moderate to high correlations at stations with more than 5 years of data. Once the seasonal cycle is removed, the correlations between anomalous monthly values in the model and observations are low to moderate (0.3–0.7), except at stations with <5 years of data, where the correlations can be lower. Correlations with available satellite observations suggest that the model is able to capture much of the observed seasonal and interannual variability in the limited regions where mineral aerosols are the dominant aerosols.

[45] In in situ observations, satellite retrievals, and model results, the variability within a month tends to be larger than the variability between different years, probably due to the event-based nature of dust transport. The model appears to have more skill in predicting interannual variability in dust in regions where there is stronger interannual variability, which is presumably a result of an increase in the signal-to-noise ratio. The amount of variability in the model appears roughly consistent with the limited available data. The model suggests that there is more variability in deposition than surface concentrations and more variability in surface concentrations than column amount.

[46] The relationship between climate indices such as the NAO, PDO, and El Niño 3.4 suggest that dust is affected by these large-scale climate phenomenon to some extent, as suggested previously [e.g., *Moulin et al.*, 1997]. However, with only a 22-year model simulation it is likely any distinctive effects of decadal oscillations such as the NAO and PDO will be less robust. Indeed observations at Barbados and the NAO are not statistically significantly correlated over this short time period, in contrast with comparisons over 1966–1996 [*Moulin et al.*, 1997]. Supporting the *Moulin et al.* [1997] hypothesis that the NAO impacts mobilization, we see a high correlation (>0.8) between the NAO and mobilization in the southern part of the North African source regions in the model. The spatial patterns in the correlations between NAO and column amount, surface concentrations, and deposition suggest that there are some changes in the transport as well. Since these correlations are ~0.6, this would imply that the NAO is associated with at most 36% of the variability (if we incorrectly assume Gaussian distributions in our variables); NAO is then an important modulator of desert dust, but much of the variability is not associated with the NAO. Both the PDO and Niño 3.4 affect modeled concentrations in the Pacific, although they have weaker correlations with desert dust than the NAO in this model. This may well be due to the fact that this model predicts over 50% of the global dust source as coming from North Africa [*Luo et al.*, 2003]. Atmospheric dust loading, even in North Africa, is more strongly correlated with NAO than El Niño, even though El Niño is shown to have strong correlations with Sahelian precipitation [e.g., *Dai and Wigley*, 2000].

[47] We estimate the "representativeness" of the different observing stations by correlating model surface concentrations at the stations with model column amount, deposition, and surface concentrations at nearby grid points to show the regions with high correlations. At all stations but Funafuti, the low to moderate correlations (>0.4) extend to suggest that the stations are monitoring interannual variability up to several hundred kilometers distant from the station. Variability in surface concentrations at the observing stations is often well correlated with column amount and surface concentration in the regions near the source. Correlations between variability in station surface concentrations and deposition tend to be low to moderate at many stations, indicating difficulty in extrapolating variability in station surface concentrations to regional deposition fluxes. We also considered the representativeness of monthly mean satellite data in inferring surface concentration, deposition, and mobilization interannual variability. A correlation of model predicted column amount and deposition at each point suggests that variability in column amount is often only low to moderately correlated with deposition (0.2–0.6). This implies that using variability in satellite-retrieved optical depths to infer variability in deposition may be difficult. Similarly, correlations between mobilization and column amount are only low to moderately correlated over most source regions (−0.2–0.6). Correlations between column amount and surface concentrations are stronger (0.4–0.8), but even the moderate correlations (0.4–0.6) seen over parts of the globe suggest that variability in satellite-retrieved optical depths only will give information about at most 16–36% of the variability in surface concentration even if the satellite retrievals have no errors. Even including the seasonal cycle (which tends to increase the correlations) results in spatial locations where surface concentrations, deposition, or mobilization are not well correlated with column amount.

[48] These results highlight the problem of having enough observations to constrain the mineral aerosol distribution and deposition flux over the globe. Because both the intramonthly and intermonthly variability is so large, high frequency and long-term measurements are required. Satellite observations are capable of providing good spatial and temporal coverage (although there are limitations with 1979–2000 satellite data as discussed above). However, our results suggest that satellite observations may be difficult to extrapolate from optical depth to surface concentrations, deposition fluxes, or mobilization. Model correlations between the spatial distributions of column amount and surface concentration are 0.85, while the correlation between spatial distributions of column amount and deposition is 0.70, and are only 0.5 (only calculated over land) for

mobilization and column amount. Correlations between variability in modeled monthly mean column amount and the modeled surface concentration, deposition and mobilization at the same point are 0.4–0.8, 0.2–0.6, and −0.2–0.6, respectively, for most of the globe. Thus only 10–75% of the temporal and spatial variability of surface concentration, deposition, and mobilization can be characterized by observing optical depths (if we assume, incorrectly, Gaussian errors, which may be a bad assumption), with deposition or mobilization being much harder than surface concentrations to observe. Analysis of the model results suggest that the in situ observation stations provide regional information about the variability in surface concentrations and optical depths, but, again, deposition is more difficult to extrapolate. Because of the strength of the wet deposition in this model, it is possible that the correlations with deposition are slightly higher in other models and the real world, but they will not be higher than the correlation with surface concentration. These results highlight the difficulty in observing mineral aerosols well enough so that even the large-scale features of the variability in distribution and deposition of mineral aerosols is documented. This will limit our ability to evaluate dust models and the subsequent calculations of radiative forcing and biogeochemical impacts.

[49] Understanding interannual variability of desert dust and our ability to simulate it in models is an important step to understanding both the importance of desert dust to climate and biogeochemistry, as well as how humans may be impacting desert dust. While in this study, the model was able to capture much of the variability seen in the observations from 1979 to 2000; a previous study [*Mahowald et al.*, 2002] showed that the same model is not able to capture changes in Barbados dust seen prior to 1979. There may be different processes that are important to be able to simulate the 1979–2000 period versus the pre-1980 period (e.g., different sources), or this may indicate that our model has difficulty simulating the period prior to the inclusion of satellite data in the reanalyses.

[50] **Acknowledgments.** We would like to thank Dennis Savoie, Joe Prospero, and Rich Arimoto for making data available to us. This manuscript benefited from comments by Ron Miller, Omar Torres, Rich Arimoto, Masaru Yoshioka, and Joe Prospero. This work was supported by NASA-IDS (NAG5-9671 (NM) and NAG5-10147 (CSZ)), NASA-NIP (NAG5-8680 (NM) and NAG5-10546 (CSZ)), and NSF-Biocomplexity (OCE-9981398 (NM)).

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