

## Article

# Wind Erosion Under a Changing Climate: Past and Future (1960–2040) Evolution in the Dust Belt

Mostafa El-Nazer <sup>1,\*</sup> , Ali Wheida <sup>1</sup> , Amira Mostafa <sup>2</sup>, Moetasm H. ElTaweel <sup>3</sup> , M. M. Abdel Wahab <sup>3</sup> ,  
Guillaume Siour <sup>4</sup>  and Stephane C. Alfaro <sup>4,\*</sup>

<sup>1</sup> National Research Centre, Cairo 12622, Egypt; awheida2010@gmail.com

<sup>2</sup> Egyptian Meteorological Authority, Cairo 11784, Egypt; amiranasser1988@gmail.com

<sup>3</sup> Astronomy, Space Science and Meteorology Department, Faculty of Science, Cairo University, Giza 12613, Egypt; moetasm@sci.cu.edu.eg (M.H.E.); magdy@sci.cu.edu.eg (M.M.A.W.)

<sup>4</sup> Univ. Paris Est Creteil and Université Paris Cité, CNRS, LISA, F-94010 Créteil, France; guillaume.siour@lisa.ipsl.fr

\* Correspondence: mostafa.elnazer@gmail.com (M.E.-N.); stephane.alfaro@lisa.ipsl.fr (S.C.A.)

## Abstract

The continuum of arid and semi-arid lands spanning from the western coast of the Sahara to the Chinese deserts (the Dust Belt) contains the most active dust sources on Earth. Understanding how their emissions are influenced by human activities and by natural climate variations is crucial for the prediction of our future climate. This work analyzes the correlation between the decadal variability in the dust surface concentrations in 23 representative sub-regions of the Dust Belt and 6 major climate oscillations. A simple parameterization assuming that this evolution can be considered a linear temporal trend, due to human activities but modulated by the effects of the natural climate variability, reproduces well ( $R^2 > 0.70$ ) the variations in the concentrations at 18 locations. In the western part of the Sahel, concentrations are large, decreasing, and influenced by the North Atlantic Oscillation (NAO, positive correlation). Conversely, concentrations increase in East and Northeast Africa where the Pacific decadal Oscillation (PDO) and the East Atlantic/Western Russia oscillations (EAWR, negative correlation) play a leading role. In Asia, the situation is more contrasted: temporal trends can be positive or negative, and are mostly modulated by the NAO (in the west) or by the EAWR (positive or negative correlation) in the south and east.

**Keywords:** Dust-Belt; wind erosion; climate variability; NAO; PDO; ENSO; East Atlantic/Western Russian Oscillation; Indian Ocean Dipole



Academic Editor: Álvaro Gómez-Gutiérrez

Received: 6 May 2026

Revised: 25 June 2026

Accepted: 29 June 2026

Published: 2 July 2026

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## 1. Introduction

Wind erosion of arid and semi-arid lands is one of the main contributors to the atmospheric loading of particulate matter (PM). Based on model studies, the current yearly emissions of mineral dust amount to between 1000 and 4000 Tg [1], and they are estimated to have increased by about 25% since the pre-industrial era because of the climate change induced by human activities and the change in land use [2].

On Earth, the largest and most persistent dust sources are located in the northern hemisphere, more precisely in the Dust Belt, a term coined by Prospero et al. [3] (2002) to designate the vast continuum of un- or poorly vegetated lands spanning from the west coast of North Africa to the deserts of north China.

In a nutshell, there are two processes involved in wind erosion: The first one, saltation, starts when the stress exerted by the wind on loose sand-sized grains outbalances the

cohesive forces maintaining them on the ground [4,5]. Because of their relatively important weight, these grains move close to the surface in a layer whose thickness is typically of the order of 0.1 to 1 m [6]. As a result of the shocks occurring in this saltation layer, much smaller particles are released from the ground or from the surface of the jumping grains: this is the sandblasting process [7]. Unlike the sand grains that mostly remain in the source region, the fine particles produced by sandblasting have diameters between 0.1 and about 20  $\mu\text{m}$ , which allows them to be easily winnowed, carried away, and sometimes transported over hundreds or thousands of kilometers (e.g., [8,9]).

The environmental consequences of wind erosion are multiple. As a result of the departure of nutrient-rich material, there is a loss of fertility in the source regions [10]. Conversely, the final deposition of these particles constitutes a precious input for some continental areas and for the oligotrophic regions of the World Ocean [11,12]. During the transport phase of the dust cycle, the air-suspended particles scatter and/or absorb solar and terrestrial radiation [13], which has a direct effect on the climate of our planet. Moreover, by serving as condensation nuclei, they may favor the formation of clouds and modify the climate indirectly [14,15].

In the surface layer of source regions, the annually averaged concentration of particles with aerodynamic diameters of less than 2.5  $\mu\text{m}$  ( $\text{PM}_{2.5}$ ) usually exceeds by far the limit ( $5 \mu\text{g m}^{-3}$ ) considered by the World Health Organization (WHO) as representing a health risk for humans [16]. Vegetation and crop yields are usually negatively affected by dust deposition (e.g., [17]), although they might in rarer cases benefit from the absorption of nutrients through their leaves [18].

Since the pioneering work of Bagnold [4], much progress has been made in the understanding of the physical processes leading to dust emission. The efficiency of saltation depends on intrinsic soil characteristics such as the size distribution of its wind-erodible (loose) grains and on the presence of non-erodible elements (stones, vegetation, etc.) protecting them against the action of the wind [19,20]. Among the meteorological factors, wind speed is obviously a major driver of wind erosion. However, by favoring the development of vegetation, the formation of crusts [21] and of inter-particle bonds [22], soil moisture also plays an important part. This combination of factors of influence explains the marked seasonal character of dust emissions: for instance, wind erosion is particularly active in spring in Northeast Africa, when strong winds blow over the region [23,24]. In the Sahel, the most important dust events are due to the advection of Saharan dust in the dry winter season and to the production of local dust just before the onset of the rain season, in May and June, when vegetation is at its lowest over natural and cultivated surfaces [25,26]. In Asia, dust storms are mostly observed in March to May in the Chinese deserts [27], and in the pre-monsoon months (also March to May) in the north of the Indian subcontinent [28]. Wind erosion is also influenced by human activities, in particular agriculture [29], and the mismanagement of regional water resources, favoring the formation of dry lake beds, which thus become active dust sources (e.g., [30,31]). Although their efficiency and ecological costs are debated [32], afforestation and the development of artificial green belts constitute an effort to limit the progression of deserts and reduce dust emissions.

Observations also reveal an important interannual variability in the dust emissions in various regions of the World. Moulin et al. [33] evidenced that year-to-year variations in the dust transport above both the Atlantic and the Mediterranean were linked to fluctuations in the North Atlantic Oscillation (NAO). Ginoux et al. [34] also showed that winter emissions in the Sahel and the NAO were positively correlated. More recently, Li et al. [35] found that the dust events of the Chinese deserts were influenced by the NAO negative phase of the previous year, and Xu et al. [36] showed that these emissions were better explained when considering a combination of the NAO and El Niño Southern Oscillation (ENSO) effects.

In their study focusing on South Asia (India and Pakistan), Banerjee et al. [37] found that dust activity in the region was controlled by the Pacific Ocean sea surface temperature (SST) between 2001 and 2010, but that the North Atlantic SST played a dominant role in the next decade.

All these results underline the need to take into account climate teleconnections, even when trying to explain the inter-annual variability in dust emissions in a specific region.

The emission of mineral dust from un-vegetated or poorly vegetated surfaces also fluctuates at longer (decadal) temporal scales. A dramatic drought episode in the Sahel lasted from 1970 to the middle of the 1980s. It was followed by re-greening [38] primarily due to an intensification of the precipitation [39], although local farmers may also have played a role by modifying their agricultural practices [40]. In East Africa, the 2000s were hotter and drier than the preceding decades, which led to a series of years with extreme levels of food insecurity [41]. These variations in climate conditions that were shown to be linked to the Indian Ocean Dipole (IOD) and to ENSO [42] must also have influenced the dust production in the region.

In summary, the decadal variability in the surface dust concentration in the various regions of the Dust Belt is expected to be modulated by climatological factors but also influenced by human activities. Note that the latter influence can be direct (land use, pastoralism, water management, etc.) but also indirect through the modification in the Earth's climate resulting from the anthropogenic forcing.

The mechanisms involved in the control of dust activity by the changing climate begin to be better understood [43]. However, to date, there has been no systematic and quantitative study of the correlation between the decadal variations in the atmospheric dust load and the most important climate oscillations that could control it. This lack of quantitative information probably explains that, as underlined by the Intergovernmental Panel on Climate Change (IPCC) in its report on land–climate interactions, there is no agreement about the direction of future changes in dust emissions [44].

The objective of this work is to fill this gap for 23 representative sub-regions of the Dust Belt. Because the focus is placed on the climatological scales, the monthly concentrations of the MERRA-2 reanalysis are first used to calculate the 10-year-filtered variations in the mean (C50) and extreme (C90) dust concentrations at these locations. Then, the correlation between these concentrations and combinations of the North Atlantic Oscillation, Pacific Decadal Oscillation (PDO), El Niño Southern Oscillation (ENSO), Arctic Oscillation (AO), East Atlantic/Western Russia oscillation (EAWR), and Indian Ocean Dipole is evaluated.

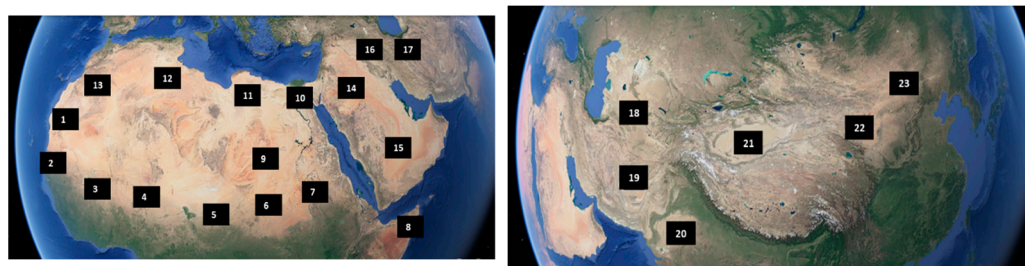
More details on the data and methodology are provided in Section 2 (Materials and Methods). In Section 3, the observational data of the 1985–2020 period are first presented and analyzed. Then, the possibility to retrieve their variations by means of a simple parametrization is assessed. In view of the good results obtained at 18 of the 23 pre-selected locations, parametrization is used to reconstruct the de-trended (of time) concentration time series over the longer period (1955–2020) of availability of the climate indices. Section 4 discusses the results and their implications for the prediction of the evolution of the dust concentration in the next decades. Finally, Section 5 draws the conclusions of this study.

## 2. Materials and Methods

### 2.1. Reanalysis Data

#### 2.1.1. Locations

In all, 23 different locations (Figure 1) were selected to represent the diversity of geographical and climatological conditions in the Dust Belt. Thirteen of them are in Africa, two in the Arabian Peninsula, and eight in Asia (for more details on their names and positions, see Table 1 of the Results section).



**Figure 1.** Positions of the locations retained for this study. The numbering of the stations is that reported in Table 1 of the Results section (the background maps are from Google Earth).

### 2.1.2. Surface Concentrations

Unfortunately, time series of dust concentration measured in situ and long enough to be used in climatological studies are quite rare. Therefore, products of reanalyses represent a precious substitute for these missing data. Among the most widely used, one can cite the global reanalysis produced by the Copernicus Atmosphere Monitoring Service (CAMS) and the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2) of the Global Modelling and Assimilation Office (GMAO 2015). The consistency of these two reanalyses for the estimates of dust surface concentration at the locations used in this study is presented in the Supplementary Materials. However, in the following, the MERRA-2 products will be preferred because they are available as of 1980, and those of CAMS only as of 2003. To differentiate these products obtained by assimilation of actual observations from the outputs of the parameterization (Equation (1)), they will be simply referred to as ‘observations’.

MERRA-2 provides estimates of the concentration of  $PM_{2.5}$  dust at the Earth’s surface. In MERRA-2, the aerosol model formed by the coupling of the Goddard Earth Observing System version 5 (GEOS-5) with the Goddard Chemistry Aerosol Radiation and Transport model (GOCART, [44,45]) is constrained by meteorological observations and by the aerosol optical depth (at 550 nm) yielded by a series of remote sensing platforms (AERONET, MODIS, AVHRR, MISR, etc.). In GOCART, the dust emissions are parameterized following the reference method of Marticorena and Bergametti [20]. The surface  $PM_{2.5}$  dust concentration (hereinafter referred to as  $C$  for simplicity) is available at a  $0.5^\circ \times 0.625^\circ$  (latitude by longitude) resolution and from 1980 onward.

For each location of this study, the monthly averages of  $C$  between January 1980 and December 2025 were extracted using the Giovanni interface (<https://giovanni.gsfc.nasa.gov/giovanni/>, accessed on 8 March 2026). Then, the 50th and 90th percentiles ( $C_{50}$  and  $C_{90}$ , respectively) of the values of each period of 10 years centered on the months between January 1985 and December 2020 were calculated. As compared to the mean concentration ( $C_{50}$ ), the added-value of  $C_{90}$  is that it documents the frequency of severe dust storms. This is necessary because, in a context of global warming under which climate extremes are becoming more frequent [46], the probability of occurrence of extreme dust events is also expected to increase faster than that of the mean emissions.

### 2.2. Indices of Decadal Climate Oscillations

The Earth’s climate is the result of complex interactions between continental surfaces, the oceans, the atmosphere, the biosphere, and the input of solar radiation, which represents the main source of energy for our planet. The climate evolves when the forcings exerted on the system are modified for natural (solar radiation, volcanism, etc.) and/or anthropogenic (emission of greenhouse gases, aerosols, land use, etc.) reasons. Paleoclimate reconstructions and measurements of the instrumental era show that time scales ranging from hours to hundreds of millennia are involved in this evolution. Only decadal scales are considered

in this work (this means that multi-decadal oscillations such as the Atlantic Multi-decadal Oscillation and the Inter-decadal Pacific Oscillation are not considered). Observations performed around the world during the 20th century reveal the existence of sea surface temperature (SST) and sea level pressure (SLP) anomalies with such decadal periodicities.

One of the oldest recognized anomalies is the North Atlantic Oscillation (NAO). There is no single way to define it [47]; essentially, its magnitude is linked to the strength of the SLP gradient between the Icelandic low and the Azores Islands high. Below-normal (above-normal) SLP in the north Atlantic high (central) latitudes corresponds to positive (negative) phases of the NAO. Storminess, precipitation, temperatures, and wind regimes in much of the northern hemisphere are significantly correlated with the NAO [48].

The Climate Prediction Center (CPC) of the National Weather Service provides time series of daily and monthly averages of a NAO index calculated following the Rotated Principal Component Analysis (RPCA) proposed by Barnston and Livezey [49]. The data are available as of January 1950. For this work, they were downloaded at the monthly resolution from the NOAA website: (<https://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml>, accessed on 30 January 2026).

SST and SLP anomalies with implications in a variety of sectors (weather, ocean oxygenation, fisheries, etc.) have also been detected in the Pacific Ocean region. The most famous one is the El Niño Southern Oscillation (ENSO), first defined by Bjerknes [50]. It mainly results from a positive feedback mechanism between the ocean and the atmosphere, leading to anomalous zonal SST gradient and surface winds (Trade Winds) over the tropical Pacific. The resulting oscillations have a typical return period of 3 to 7 years. About 30 years later, Mantua et al. [51] defined the lower-frequency phenomenon that they labeled Pacific Decadal Oscillation (PDO). The PDO is sometimes referred to as the “long-lived El Niño-like pattern of Pacific climate variability” [52].

A series of ENSO indices is proposed on the NOAA website (<https://psl.noaa.gov/data/climateindices/>, accessed on 30 January 2026). We retained the BEST index [53] that improves the Niño 3.4 index by combining it with the Southern Oscillation Index and is provided at the monthly resolution from January 1948 onward. For the PDO, we used the index also made available by the NOAA at the same temporal resolution (<https://www.ncei.noaa.gov/pub/data/cmb/ersst/v5/index/ersst.v5.pdo.dat>, accessed on 30 January 2026).

At higher latitudes of the northern hemisphere, the Arctic Oscillation (AO) corresponds to a weakening (negative phase) or strengthening (positive phase) of the belt of zonal winds that circulate the globe at about 55° N. This annular circulation is similar to that of the southern hemisphere (Southern Annular Mode, or SAM) whose winds also blow from west to east around the Antarctic. In the negative phases of the AO, intrusions of cold polar air into the mid-latitudes are facilitated, and storms become more frequent. An AO index is derived from the analysis of the daily anomalies of the 1000 hPa height between 20 and 90° N. Monthly values of this index for 1950–2025 were downloaded from the same NOAA website as that used for the NAO ([https://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily\\_ao\\_index/ao.shtml](https://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ao.shtml); accessed on 30 January 2026).

Another pattern identified by Barnston and Livezey [50] in their analysis of the low-frequency atmospheric variability is associated with 4 height anomaly centers located over the central north Atlantic, Europe, West Russia, and Northern China. For simplicity, this quadri-polar oscillation is usually referred to as the East Atlantic/West Russia (EAWR, in the following) pattern. The EAWR is in a positive phase when height anomalies are (1) positive over Europe and Northern China, and (2) negative over the Atlantic and west Russia. During the EAWR positive phases, positive surface temperature anomalies are observed over eastern Asia, and negative ones over large portions of western Russia and

Northeast Africa. Precipitations are also affected [54]. The EAWR index used in this work is again that of NOAA. Monthly values for 1950–2025 were downloaded from: [https://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/eawr\\_index.tim](https://ftp.cpc.ncep.noaa.gov/wd52dg/data/indices/eawr_index.tim) (accessed on 30 January 2026).

More recently, a dipolar mode of climate variability was discovered over the Indian Ocean [55,56]. It corresponds to the seesawing of SST between the western part of the Indian Ocean and its eastern part, off Sumatra, accompanied by anomalies in surface winds and precipitation. The climate impacts of this IOD oscillation are not limited to the immediate vicinity of the Indian Ocean. Land surface anomalies and reduced rainfall in Europe, Northeast Asia, North and South America, and South Africa have been associated with positive phases of the IOD [57]. These positive phases correspond to warmer-than-usual surface waters along the east Africa coast (50–70° E and 10° S–10° N), and cooler-than-usual ones in the southeastern equatorial Indian Ocean (90–110° E and 10° S–0° N). This SST gradient is used by the NOAA Physical Science Laboratory to produce a monthly IOD index. Data are available as of 1870 until April 2025. However, to be consistent with the time series of other indices, only the data of 1950–2025 were downloaded from: ([https://psl.noaa.gov/gcos\\_wgsp/Timeseries/Data/dmi.had.long.data](https://psl.noaa.gov/gcos_wgsp/Timeseries/Data/dmi.had.long.data), accessed on 30 January 2026).

The major modes of climate variability listed above are not fully independent. Saji et al. [56] originally considered that the IOD was unique and inherent to the Indian Ocean, but it is now more widely accepted that ENSO contributes to triggering it, or at least to reinforcing it (e.g., [58–61]). It has also been discussed in the literature how strongly the AO was related to the NAO (e.g., [62,63]) or to the PDO [64,65]. In their analysis of the PDO/ENSO relationship, Juanxiong et al. [66] found that there was a good correlation at the 2–7-year timescales but not at lower frequencies. All this suggests that there will be significant correlations between the time series of at least some of the indices retained for this study.

The 10-year averaging procedure already used with the concentrations was also applied to the time series of monthly indices between 1950 and 2025.

### 2.3. Statistical Correlation Between Surface Dust and Climate Oscillations

In the following, the two main assumptions are that (1) the effect of the global warming, and possibly of other human activities, is to induce a progressive shift in the concentration time series, and (2) this evolution is modulated as a result of the low-frequency (decadal) internal variability in the Earth's climate system. The simplest way to represent this mathematically is to consider that C50 and C90 are the products of two linear functions: one of time, and the other of the de-trended climate indices.

This yields:

$$C_x = C_{x,0}(1 + \alpha(t - t_0))(1 + a_1\text{NAO}_{\text{det}} + a_2\text{PDO}_{\text{det}} + a_3\text{AO}_{\text{det}} + a_4\text{ENSO}_{\text{det}} + a_5\text{EAWR}_{\text{det}} + a_6\text{IOD}_{\text{det}}) \quad (1)$$

In this expression, C<sub>x</sub> stands for either C50 or C90; the subscript 'det' in the indices is to recall that they are de-trended and represent only the internal variability in the climate system. 1 January 1985 is chosen as the origin of time (t<sub>0</sub>), and C<sub>x,0</sub> is the value that the concentration would have at t<sub>0</sub> were all the de-trended indices to be simultaneously nil. Slope  $\alpha$  quantifies the sensitivity of a region to the overall anthropogenic forcing, which includes, at the same time, the effects of the changing climate and those of the evolution of more regional practices (land use, agriculture, pastoralism, etc.). The coefficients  $a_1$  to  $a_6$  represent the sensitivity of the dust concentration to each decadal oscillation. C<sub>x,0</sub>,  $\alpha$ , and the  $a_i$  are initially unknown, but they can be determined by applying a least-square routine meant to adjust Equation (1) to the 432 monthly observations of the 1985–2020 period. The goodness of fit is quantified by the coefficients of correlation (R) or of determination (R<sup>2</sup>) obtained when comparing the calculated and measured concentrations. Other classical

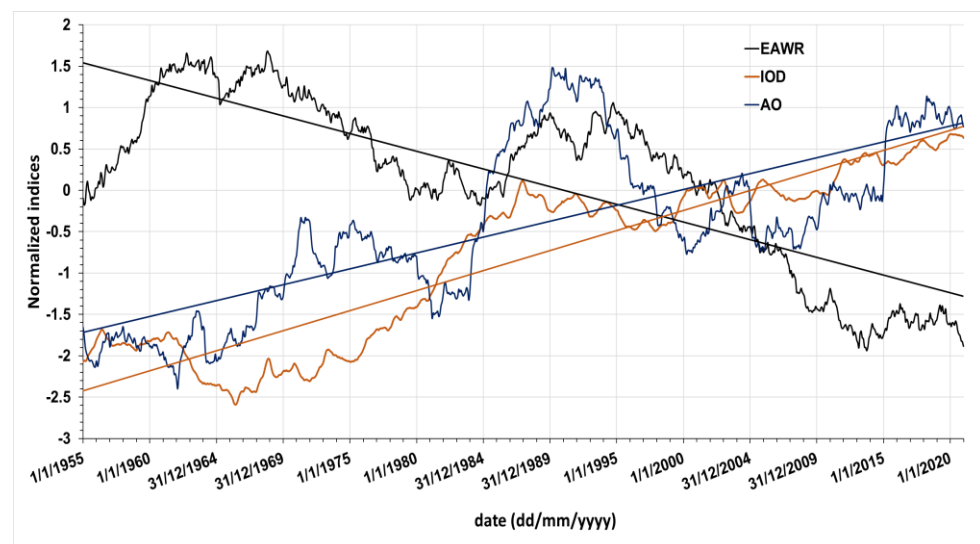
statistical indicators, such as the root mean square error (RMSE), the bias, and the relative mean absolute error (rMAE), will also be calculated. Practically, the assumptions underlying Equation (1) will be considered validated if  $R > 0.84$  ( $R^2 > 0.70$ ), which is to say if at least 70% of the variability in C50 and C90 can be explained by the dependence on time and the collective effect of the decadal oscillations.

Once validated for a given region, the first advantage of Equation (1) is that it separates the effects of the internal climate variability from those of human activities. Secondly, it allows for a numerical comparison of the individual effects of each oscillation, or of a combination thereof. Therefore, the oscillations with the largest influence in a region can be easily identified. Finally, because the climate indices are available as of 1950, Equation (1) can be extrapolated to document the variability in the surface concentrations between 1955 and 2020, and not just between 1985 and 2020, which is the more limited period of availability of the observations.

### 3. Results

#### 3.1. Decadal Oscillations

To homogenize their ranges of variation and thus facilitate their comparison, the climate indices were first divided by the standard deviation of their values in the period 1955–2020. After this normalization, the examination of the times-series of 10-year-filtered indices reveals clear temporal trends (Figure 2), which can be negative (−43%/decade for EAWR) or positive (48 and 38%/decade for the IOD and AO, respectively). Comparatively, the rates of evolution of the NAO, PDO, and ENSO (not reported on Figure 2 for legibility) appear as much slower: they are −8, −8, and 3%/decade, respectively. These results suggest that, during the last 65 years, the 10y averages of the EAWR, IOD, and AO indices were more sensitive to the anthropogenic forcing than those of the NAO, PDO, and ENSO.

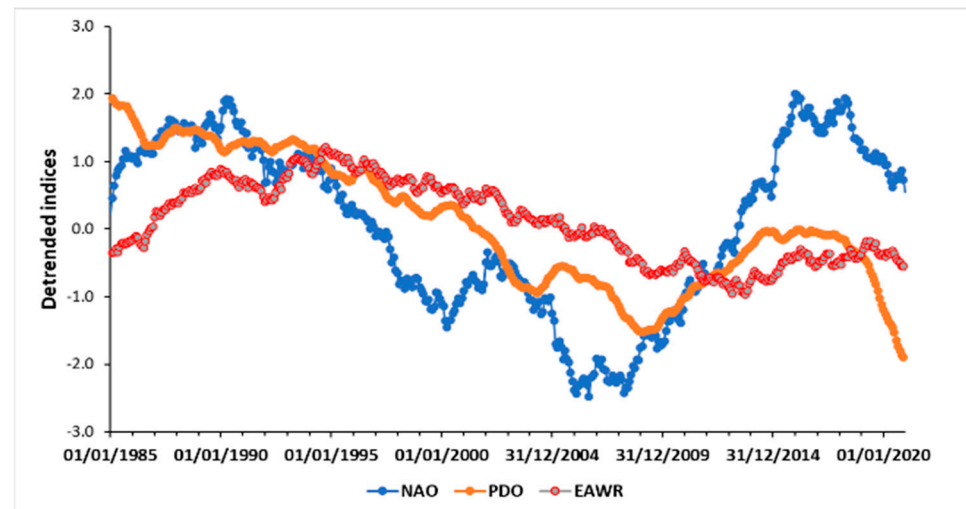


**Figure 2.** Time series of the 10-year sliding averages of the indices of major climate oscillations. EAWR stands for the Eastern Atlantic/Western Russian oscillation, IOD for the Indian Ocean Dipole, and AO for the Arctic Oscillation.

The analysis of the actual correlation between the oscillations is biased by the existence of these temporal trends. For instance, between 1955 and 2020, the EAWR and IOD were strongly and negatively correlated ( $R = -0.76$ ), but after de-trending, this correlation disappears ( $R = -0.04$ ). Conversely, de-trending does not modify the strong correlation between the PDO and ENSO ( $R = 0.80$ ) and even strengthens that between the NAO and the AO ( $R$  increases from 0.34 to 0.67). These correlations suggest that it will be difficult

to separate the influences of the PDO and ENSO (resp. NAO and AO) internal modes of variability on the decadal variations in the dust emission in the Dust Belt.

Focusing on the 1985–2020 period for which the 10-year-filtered concentrations are available, it can be observed that the temporal evolutions of the NAO, PDO, and EAWR indices (de-trended over 1955–2020, as in Figure 2) were not in phase (Figure 3). All three indices decreased after 1990, but the NAO achieved its minimal value around 2005, the PDO about 2 to 3 years later, and the EAWR around 2013.



**Figure 3.** Temporal evolutions between 1985 and 2020 of the 10-year filtered and de-trended NAO, PDO, and EAWR indices.

### 3.2. Analysis of the Surface Concentrations

Between 1985 and 2020, the decadal mean PM<sub>2.5</sub> dust concentration (C<sub>50</sub>) exceeded the 5  $\mu\text{g m}^{-3}$  guideline of the WHO at all the 23 locations selected for this study (Table 1). Maximal concentrations were observed in the Arabian Peninsula (Saudi Arabia south), the Sahel (from Dakar to Khartoum), North Africa (from Tindouf to Libya), and in the Taklamakan and Turkmenistan Asian deserts.

**Table 1.** Number, positions (lat., lon., both in decimal degrees), and name of the 23 locations selected for this study. The means of C<sub>50</sub> and C<sub>90</sub> for the 1985–2020 period are in  $\mu\text{g m}^{-3}$ . The slopes (Sl<sub>C<sub>50</sub></sub> and Sl<sub>C<sub>90</sub></sub>) are indicated in both  $\mu\text{g m}^{-3}/\text{decade}$  and  $\%/decade$ .

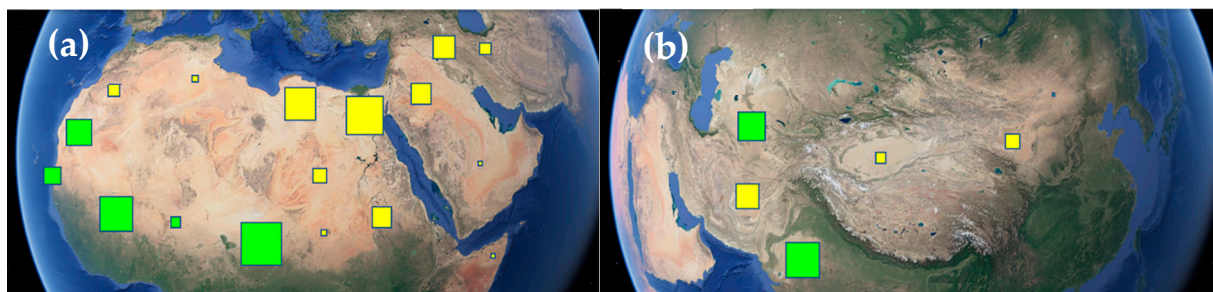
| REGION | Location | lat. (°) | lon. (°) | Name                 | C50 | Sl <sub>C50</sub> |       | C90 | Sl <sub>C90</sub> |       |
|--------|----------|----------|----------|----------------------|-----|-------------------|-------|-----|-------------------|-------|
| WASa   | 1        | 25.0     | −13.0    | Western Sahara       | 60  | −1.85             | −3.1% | 95  | −3.16             | −3.3% |
|        | 2        | 14.8     | −17.0    | Dakar                | 50  | −2.37             | −4.5% | 100 | −2.18             | −2.1% |
|        | 3        | 12.5     | −8.0     | Bamako               | 38  | −1.52             | −3.9% | 69  | −4.17             | −5.7% |
|        | 4        | 13.5     | 2.0      | Niamey               | 67  | −2.30             | −3.4% | 133 | −1.22             | −0.9% |
|        | 5        | 12.0     | 15.0     | Ndjamena             | 77  | −2.86             | −4.0% | 169 | −5.01             | −2.9% |
|        | 6        | 13.5     | 24.5     | El Fasher            | 32  | −0.77             | −2.4% | 43  | 0.72              | 1.7%  |
| NEAME  | 7        | 15.5     | 32.5     | Khartoum             | 86  | 0.45              | 0.5%  | 112 | 2.41              | 2.2%  |
|        | 8        | 9.5      | 49.0     | Somalia              | 22  | 1.26              | 6.1%  | 51  | 0.79              | 1.6%  |
|        | 9        | 22.0     | 23.0     | Libya (SE)           | 49  | 2.11              | 4.7%  | 68  | 1.73              | 2.7%  |
|        | 10       | 30.0     | 31.0     | Cairo                | 21  | 1.94              | 10.1% | 40  | 4.73              | 12.4% |
|        | 11       | 29.0     | 23.0     | Libya (N)            | 67  | 2.28              | 3.6%  | 91  | 3.84              | 4.5%  |
|        | 12       | 31.0     | 8.0      | GW Sand Sea          | 69  | 0.42              | 0.6%  | 100 | 0.84              | 0.9%  |
|        | 13       | 31.0     | −8.0     | Tindouf              | 71  | 0.63              | 0.9%  | 94  | 1.40              | 1.5%  |
|        | 14       | 29.0     | 41.0     | Saudi Arabia (N)     | 34  | 1.05              | 3.3%  | 44  | 2.52              | 6.1%  |
|        | 15       | 20.0     | 50.0     | Saudi Arabia (S)     | 99  | 1.09              | 1.1%  | 139 | 0.05              | 0.0%  |
|        | 16       | 32.0     | 51.0     | Isfahan              | 17  | 0.21              | 1.3%  | 25  | 2.13              | 9.1%  |
|        | 17       | 33.0     | 54.0     | Dasht-e Kavir Desert | 22  | 0.84              | 4.2%  | 34  | 1.48              | 4.8%  |

Table 1. Cont.

| REGION        | Location | lat. (°) | lon. (°) | Name           | C50 | Sl.C50 |       | C90 | Sl.C90 |       |
|---------------|----------|----------|----------|----------------|-----|--------|-------|-----|--------|-------|
| ASIA<br>(S&E) | 18       | 40.0     | 60.0     | Turkmenistan   | 63  | −0.33  | −0.5% | 93  | −3.18  | −3.4% |
|               | 19       | 30.0     | 65.0     | Kandahar       | 28  | 1.27   | 4.6%  | 38  | 2.83   | 7.3%  |
|               | 20       | 28.0     | 72.0     | Thar           | 45  | −2.63  | −6.1% | 109 | −4.13  | −3.8% |
|               | 21       | 40.0     | 81.0     | Taklamakan     | 81  | 1.54   | 1.9%  | 122 | 1.20   | 0.9%  |
|               | 22       | 40.0     | 102.0    | Gobi           | 33  | 0.24   | 0.7%  | 43  | 1.70   | 4.3%  |
|               | 23       | 42.0     | 112.0    | Inner Mongolia | 9   | −0.47  | −4.6% | 17  | −0.31  | −1.7% |

In the same period, the average rates of temporal variation in C50 and C90 ranged from  $-5$  to  $+5 \mu\text{g m}^{-3}$  per decade (Table 1). These rates of evolution are linearly correlated ( $R^2 = 0.75$ ), and the slope of 1.49 indicates that, in absolute value, C90 increased (or decreased) about 50% faster than C50 in the Dust Belt. This difference is mostly due to the fact that C90 is larger than C50 and, in relative values, the rates of evolution of C50 and C90 are comparable (slope = 0.98,  $R^2 = 0.72$ ).

Based on these rates of evolution, clear regional differences are observed in the North African/Middle East continuum (Table 1 and Figure 4a). The concentrations tended to decrease rapidly in West Africa and the Sahel, a region simply named the WASa in the following. Conversely, concentrations increased in Northeast Africa, the Arabian Peninsula, and from Iran to the Registan desert (Kandahar) in western Afghanistan. Hereinafter, this vast region will be referred to as the Northeast Africa/Middle East (NEAME). In the south and east of Asia (Asia (S&E), for short), the situation was more contrasted with concentrations decreasing sharply in Turkmenistan and the Thar deserts, but increasing modestly in the Chinese (Taklamakan and Gobi) ones (Figure 4b). They decreased slightly in Inner Mongolia.

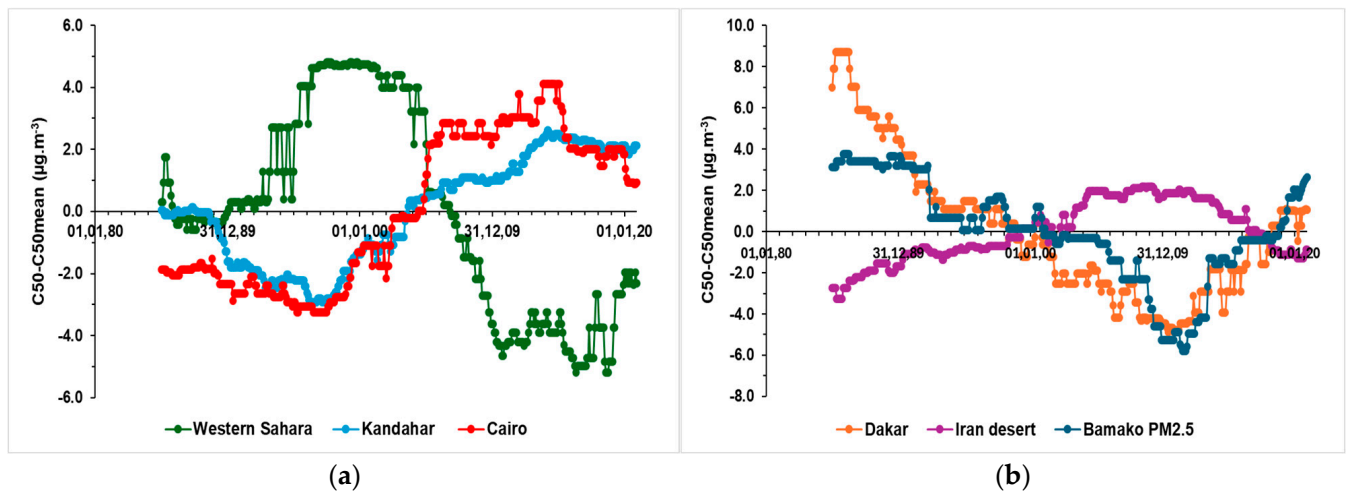


**Figure 4.** Temporal trends of the 90th percentile of the surface PM<sub>2.5</sub> dust concentrations in the western (a) and eastern (b) parts of the Dust Belt. The size of the squares is proportional to the rate of increase (in yellow) or of decrease (in green) reported in Table 1.

These results show that North African sources cannot be considered as a whole when trying to explain the variability in their emissions by anthropogenic influences and climate drivers. A transition zone spanning from Morocco to South Sudan, and going through Tindouf, the Great Eastern Sand Sea, and El Fasher seems to serve as a buffer between the WASa and NEAME regions. However, even within these two great sub-regions, different rates of evolution of the surface dust concentrations suggest differences in sensitivity to the ongoing climate warming. For instance, in Northeast Africa, the locations closest to the Mediterranean Sea (North Libya and Cairo) are characterized by a faster increase in the dust concentrations than those more in the south (South-East Libya and Khartoum).

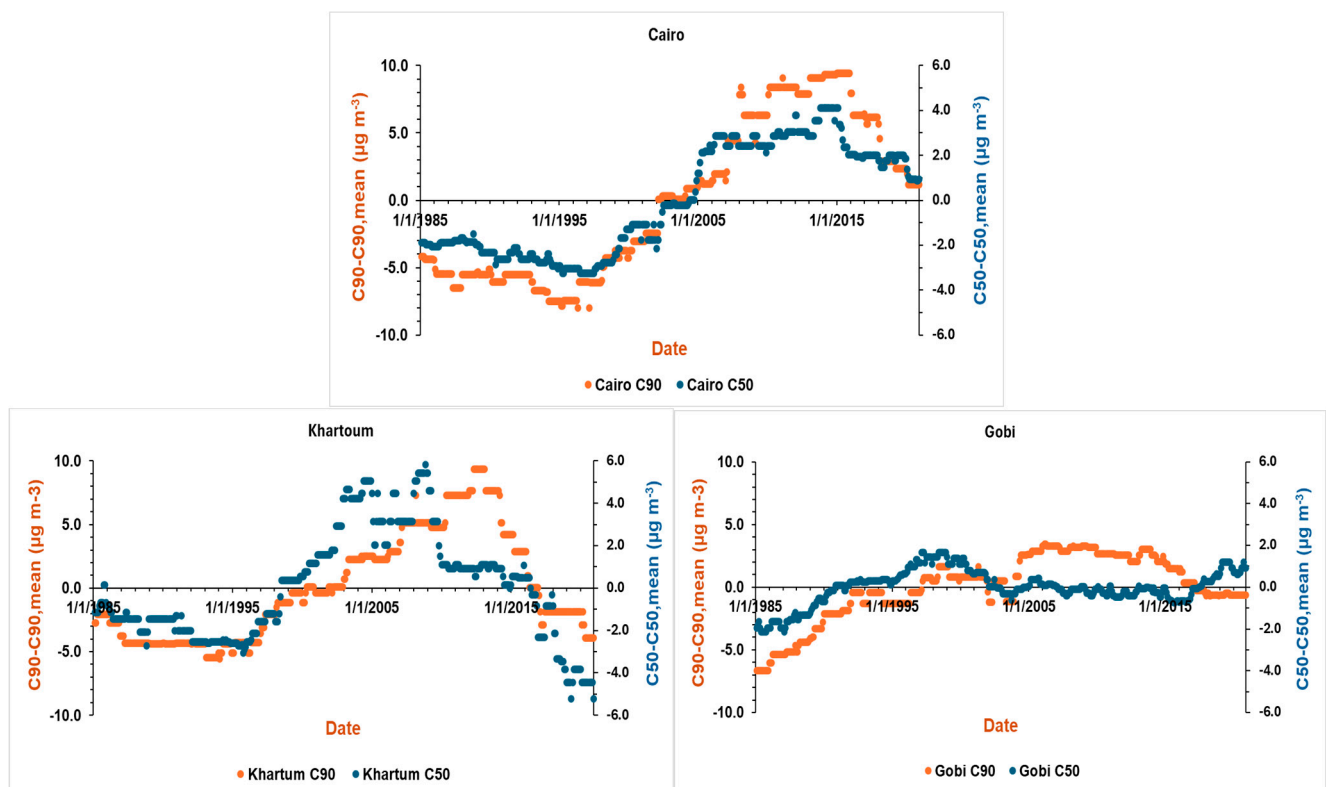
The comparison of the temporal patterns of C50 at the different locations is also revealing. For instance, the time series of Cairo and the Western Sahara are almost in phase opposition (Figure 5a) whereas those of Cairo and Kandahar are very similar despite the considerable distance (ca. 3200 km) separating them. Also, the evolutions of the

concentrations in Dakar and Bamako follow the same trend but are opposite to that of the Dasht-e Kavir Desert (more simply referred to as the ‘Iran Desert’ in Figure 5b and the following). This suggests that the same climate drivers might be at play in the different regions, but with influences having similar or opposite signs.



**Figure 5.** Comparison of the temporal evolutions of the decadal mean dust concentrations (C50) at 6 different locations of the Dust Belt.

At a given location, C50 and C90 may co-vary (e.g., in Cairo), but they may also be out of phase (e.g., in Khartoum or the Gobi Desert) (Figure 6). This suggests that, at least in some regions, the dust events of moderate intensity and those more extreme might be sensitive to different climate features.



**Figure 6.** Temporal evolutions of C50 and C90 at 3 different locations.

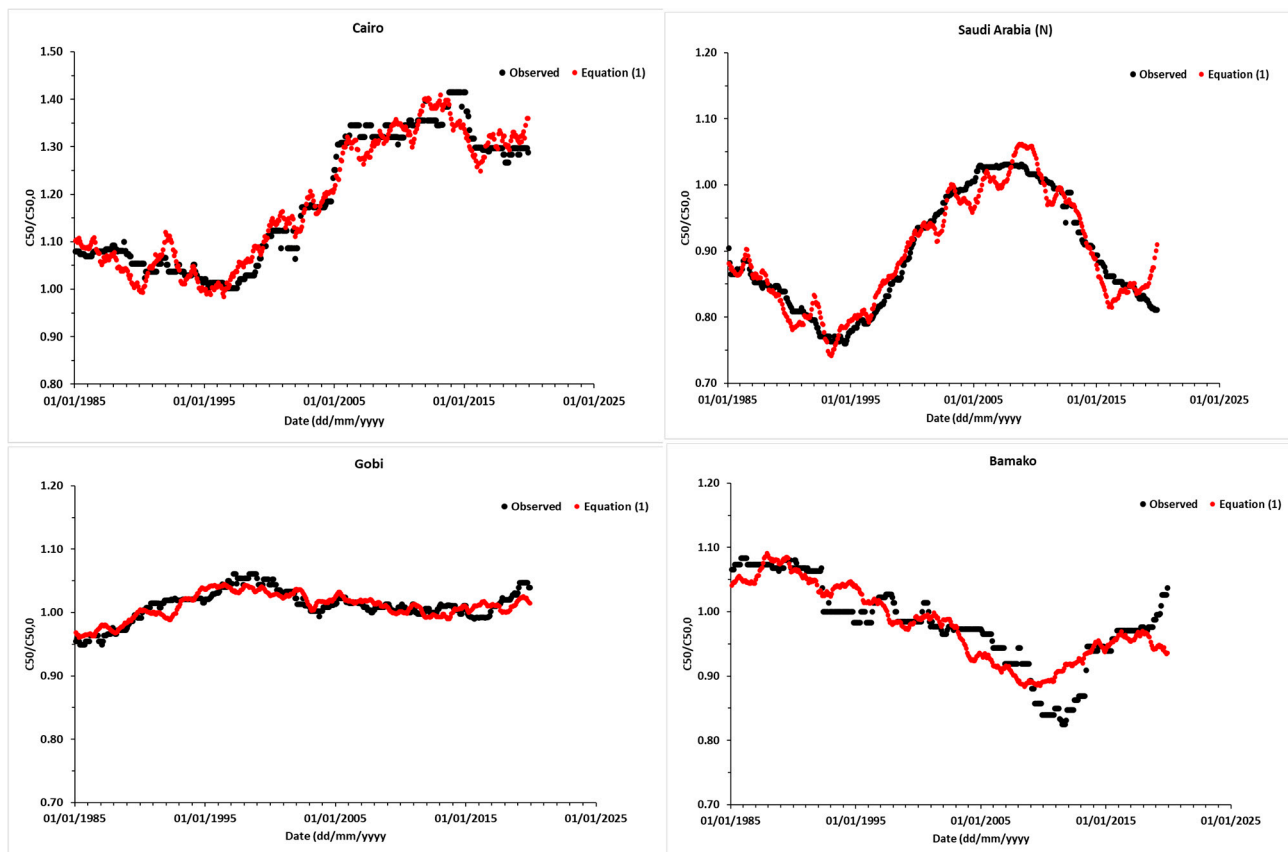
### 3.3. Parameterization of the Variability in the Surface Concentrations Between 1985 and 2020

The ability of Equation (1) to reproduce the temporal variations in C50 and C90 between 1985 and 2020 was evaluated for all the locations of this study. As indicated in the methodology section, these tests were considered as successful if at least 70% of the variability in both C50 and C90 could be explained by the parameterization. This was found to be the case at 9 of the 11 locations of the NEAME and 5 of the 6 locations of the WASa (Table 2). In the rest of Asia, the results were found to be satisfactory at four of the six sites. In all, 18 of the 23 preselected locations met the  $R^2$  criteria. At these locations, the average RMSE is less than  $2 \mu\text{g m}^{-3}$ , the bias ( $<1 \mu\text{g m}^{-3}$ ) is negligible, and the rMAE is very low ( $<2\%$ ). All this validates the assumptions underlying Equation (1), namely that the low-frequency fluctuations in the dust concentration around the temporal trend are primarily driven by the decadal oscillations of the Earth's climate.

**Table 2.** Results of the adjustment using Equation (1) to the observations of C50 (a) and C90 (b). Only the 18 locations that passed the goodness-of-fit test (see text for more details) are reported.

| (a)           |    | C50              | CX,0   | $\alpha$<br>(%/Decade) | a1    | a2    | a3    | a4    | a5    | a6    | R <sup>2</sup> | RMSE | Bias  | rMAE |
|---------------|----|------------------|--------|------------------------|-------|-------|-------|-------|-------|-------|----------------|------|-------|------|
| WASa          | 1  | Western Sahara   | 62.89  | −3.2%                  | 0.05  | −0.01 | −0.27 | −0.03 | 0.37  | −0.05 | 0.85           | 1.3  | 0.01  | 1.5% |
|               | 2  | Dakar            | 49.69  | −4.3%                  | 0.15  | 0.07  | −0.09 | −0.05 | −0.06 | 0.05  | 0.87           | 1.2  | 0.01  | 1.8% |
|               | 3  | Bamako           | 36.96  | −1.7%                  | 0.13  | 0.02  | −0.11 | −0.03 | 0.18  | 0.34  | 0.76           | 1.2  | 0.01  | 2.5% |
|               | 4  | Niamey           | 69.32  | −3.8%                  | 0.02  | −0.10 | 0.03  | 0.03  | 0.06  | 0.28  | 0.74           | 1.6  | 0.01  | 1.7% |
|               | 6  | El Fasher        | 33.34  | −3.4%                  | −0.08 | −0.05 | 0.06  | −0.06 | 0.05  | 0.05  | 0.79           | 0.6  | −0.01 | 1.3% |
| NEAME         | 7  | Khartoum         | 84.74  | −0.1%                  | −0.07 | 0.00  | 0.02  | −0.11 | 0.04  | 0.15  | 0.70           | 1.3  | −0.02 | 1.3% |
|               | 8  | Somalia          | 21.00  | 2.2%                   | 0.09  | −0.09 | −0.07 | −0.12 | −0.11 | 0.44  | 0.91           | 0.5  | 0.00  | 1.8% |
|               | 9  | Libya (SE)       | 47.82  | 2.9%                   | −0.14 | −0.08 | −0.04 | −0.01 | 0.01  | 0.34  | 0.91           | 1.1  | −0.01 | 1.7% |
|               | 10 | Cairo            | 17.83  | 10.3%                  | −0.20 | 0.01  | 0.17  | 0.04  | −0.54 | 0.59  | 0.94           | 0.6  | 0.00  | 2.8% |
|               | 11 | Libya (N)        | 63.33  | 1.9%                   | −0.13 | −0.07 | 0.03  | −0.04 | −0.14 | 0.51  | 0.89           | 1.4  | −0.01 | 1.7% |
|               | 14 | Saudi Arabia (N) | 35.48  | −4.9%                  | −0.06 | −0.24 | −0.18 | −0.06 | −0.21 | 0.66  | 0.93           | 0.8  | −0.01 | 1.8% |
|               | 15 | Saudi Arabia (S) | 96.97  | 1.2%                   | −0.19 | 0.00  | 0.19  | 0.00  | −0.10 | 0.00  | 0.78           | 1.8  | −0.01 | 1.5% |
|               | 16 | Isfahan          | 16.90  | 0.3%                   | −0.14 | 0.03  | 0.11  | −0.08 | −0.11 | −0.01 | 0.78           | 0.3  | 0.00  | 1.4% |
| ASIA<br>(S&E) | 17 | Iran Desert      | 21.26  | 3.7%                   | −0.18 | −0.04 | 0.12  | 0.02  | −0.05 | 0.06  | 0.85           | 0.6  | −0.01 | 1.9% |
|               | 19 | Kandahar         | 26.36  | 2.3%                   | 0.05  | −0.04 | −0.02 | −0.04 | −0.28 | 0.39  | 0.91           | 0.5  | 0.00  | 1.6% |
|               | 20 | Thar             | 42.46  | −2.3%                  | 0.12  | 0.03  | −0.35 | −0.06 | 0.44  | 0.63  | 0.87           | 1.2  | 0.01  | 2.4% |
|               | 22 | Gobi             | 33.92  | 0.6%                   | 0.00  | −0.01 | −0.07 | 0.06  | 0.12  | −0.21 | 0.71           | 0.5  | −0.03 | 1.1% |
|               | 23 | Inner Mongolia   | 9.83   | −11.4%                 | 0.27  | −0.11 | −0.37 | −0.26 | −0.35 | 0.91  | 0.84           | 0.3  | 0.00  | 2.9% |
| (b)           |    | C90              | CX,0   | $\alpha$<br>(%/decade) | a1    | a2    | a3    | a4    | a5    | a6    | R <sup>2</sup> | RMSE | Bias  | rMAE |
| WASa          | 1  | Western Sahara   | 97.08  | −3.6%                  | 0.02  | −0.05 | −0.02 | −0.06 | 0.15  | 0.19  | 0.89           | 1.2  | 0.01  | 1.1% |
|               | 2  | Dakar            | 105.84 | −2.3%                  | 0.27  | 0.06  | −0.12 | 0.03  | 0.00  | −0.52 | 0.90           | 2.3  | −0.66 | 1.8% |
|               | 3  | Bamako           | 74.68  | −4.9%                  | 0.08  | 0.01  | 0.03  | 0.01  | 0.09  | −0.27 | 0.95           | 1.1  | 0.00  | 1.0% |
|               | 4  | Niamey           | 139.25 | −1.4%                  | 0.07  | −0.05 | 0.11  | 0.09  | −0.04 | −0.25 | 0.72           | 2.5  | −0.15 | 1.4% |
|               | 6  | El Fasher        | 43.15  | 1.6%                   | −0.20 | 0.05  | 0.11  | 0.07  | −0.21 | −0.25 | 0.74           | 1.0  | −0.12 | 1.8% |
| NEAME         | 7  | Khartoum         | 109.64 | 1.4%                   | −0.10 | 0.03  | 0.05  | −0.06 | −0.14 | 0.07  | 0.83           | 1.7  | −0.03 | 1.2% |
|               | 8  | Somalia          | 50.48  | 0.9%                   | −0.03 | −0.02 | −0.07 | −0.03 | 0.03  | 0.21  | 0.70           | 0.8  | 0.00  | 1.3% |
|               | 9  | Libya (SE)       | 66.25  | 2.7%                   | −0.11 | −0.06 | 0.14  | 0.03  | −0.02 | 0.16  | 0.87           | 1.0  | 0.02  | 1.1% |
|               | 10 | Cairo            | 33.50  | 15.1%                  | −0.21 | 0.15  | 0.26  | −0.18 | −0.48 | 0.25  | 0.93           | 1.6  | −0.07 | 3.4% |
|               | 11 | Libya (N)        | 83.95  | 5.0%                   | −0.21 | −0.05 | 0.13  | 0.03  | −0.16 | 0.49  | 0.88           | 2.1  | −0.01 | 2.0% |
|               | 14 | Saudi Arabia (N) | 44.14  | −0.6%                  | −0.08 | −0.09 | −0.15 | −0.08 | −0.30 | 0.34  | 0.94           | 1.1  | −0.01 | 1.9% |
|               | 15 | Saudi Arabia (S) | 137.75 | −0.1%                  | −0.09 | 0.00  | 0.23  | 0.05  | −0.25 | −0.04 | 0.70           | 1.9  | 0.03  | 1.1% |
|               | 16 | Isfahan          | 23.37  | 6.4%                   | −0.22 | −0.03 | 0.19  | −0.05 | −0.34 | 0.18  | 0.94           | 0.7  | 0.00  | 2.3% |
| ASIA<br>(S&E) | 17 | Iran Desert      | 34.44  | 3.6%                   | −0.14 | −0.04 | 0.07  | 0.03  | 0.05  | −0.13 | 0.89           | 0.7  | 0.00  | 1.7% |
|               | 19 | Kandahar         | 36.19  | 2.9%                   | 0.19  | −0.04 | −0.12 | −0.09 | −0.39 | 0.38  | 0.92           | 1.1  | 0.00  | 2.4% |
|               | 20 | Thar             | 111.45 | −4.0%                  | 0.14  | −0.08 | −0.26 | −0.08 | 0.31  | 0.42  | 0.72           | 3.1  | 0.48  | 2.2% |
|               | 22 | Gobi             | 40.97  | 7.6%                   | −0.24 | 0.07  | 0.18  | 0.04  | 0.00  | −0.15 | 0.86           | 1.0  | −0.01 | 1.8% |
|               | 23 | Inner Mongolia   | 19.29  | −11.7%                 | 0.27  | −0.10 | −0.33 | −0.09 | −0.69 | 0.15  | 0.75           | 0.7  | −0.02 | 2.8% |

To further illustrate the quality of the adjustments, Figure 7 compares the observed and retrieved temporal evolutions of the C50/C50,0 ratios at four locations in completely different regions (Cairo, North Saudi Arabia, Bamako, and Gobi).



**Figure 7.** Examples of comparisons of the observed time series of mean surface dust concentration normalized by C50,0 and the results of Equation (1) (note the difference in vertical scale for Cairo).

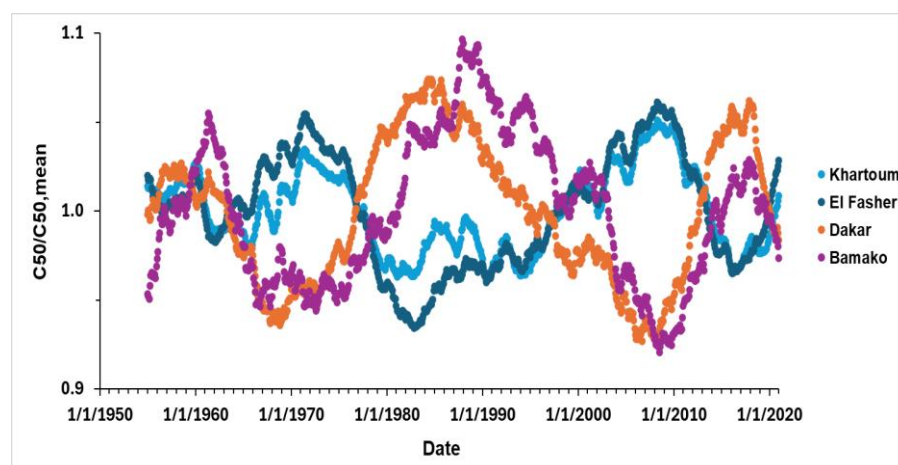
The negative values of  $\alpha$  obtained for both C50 and C90 along the west African coast and in the western part of the Sahel (Western Sahara, Dakar, Bamako, Niamey) indicate that the ongoing climate change tends to reduce dust production in this region. The effect is opposite in the NEAME, where  $\alpha$  is positive everywhere but in the north of Saudi Arabia. It is worth noting that this negative sign is not contradictory with the increase in the concentrations observed there between 1985 and 2020 (cf. Table 1). Indeed, the overall temporal evolution of the concentrations depends not only on the sign and magnitude of  $\alpha$ , but also on the variations in the climate indices, a second effect which, over a limited period of observation, may outbalance the first one.

The sensitivity of the concentrations to the de-trended indices also follows specific regional patterns. In West Africa and in South and East Asia,  $a1$  and  $a5$  are mostly positive, whereas they are negative in the NEAME area (Table 2). This indicates opposite influences of the NAO and EAWR oscillations. This point will be studied in more detail in the Discussion section (Section 4).

### 3.4. Reconstruction of the Temporal Evolution of C50 and C90 After 1955

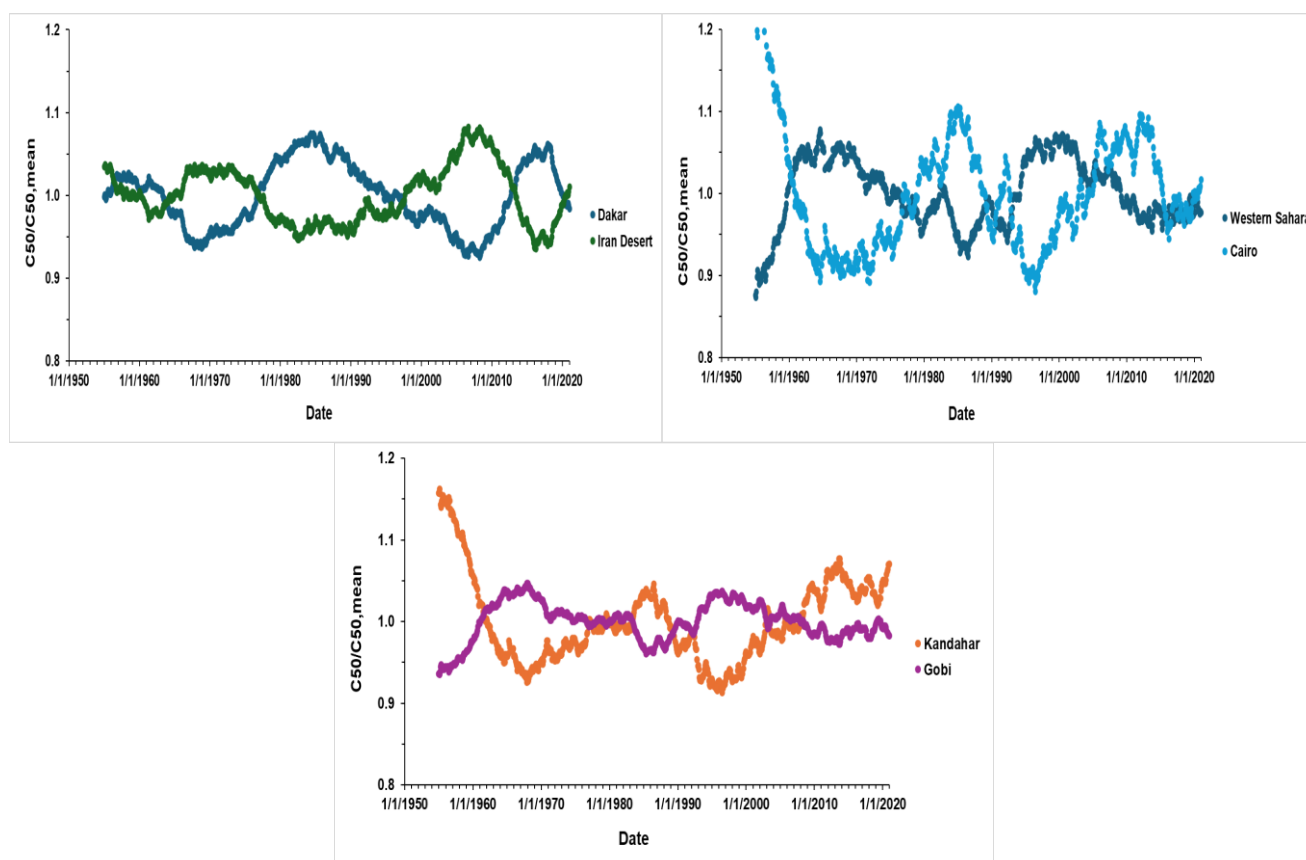
The advantage of using Equation (1) for reconstructing the variations in the concentrations over a longer period than that of the observations is that this offers the possibility to simulate several successive decadal cycles and put the observations in a larger frame. For instance, it appears that the decrease in the concentrations observed between 1985 and 2009 in West Africa (Dakar, Bamako) corresponds to the end of a cycle that had started around 1970, culminated in the 80s, and ended in 2010. The peak of this cycle, even easier to discern after removal of the temporal trend and normalization by C50,0 (Figure 8), coincides with the drought that struck the western part of the Sahel in this period. Further east, in Sudan

(El Fasher and Khartoum), the largest concentration maxima occurred around 1970 and 2010, years that correspond to the lows in the time series of the western Sahel.



**Figure 8.** De-trended time series of the  $C50/C50,0$  ratio at 4 different locations. These results were obtained by extrapolation of Equation (1) to the 1955–2020 period.

Similar quasi-perfect phase oppositions are observed between the western and north-eastern parts of the Sahara (Western Sahara and Cairo, respectively), between the western Sahel and Iran (Dakar and Iran Desert), and between the Registan (Kandahar) and the Gobi deserts (Figure 9).



**Figure 9.** Same as Figure 8, but with different locations. The purpose is to further illustrate the opposition of phase between the  $C50$  time series of sub-regions of the Dust Belt.

Another interesting point of Figures 8 and 9 is that they allow for visualizing the range of variation in the C50/C50,0 ratio. Most of the values are between 0.9 and 1.1, which means that the amplitude of the oscillations that could be attributed to the internal variability in the climate system rarely exceeded 10% in the 1955–2020 period. A more precise estimation of this amplitude can be obtained for each site, and separately for C50 and C90, by calculating the interval between the 95th and 5th percentiles of the statistical distributions of the CX/X,0 ratios.

When trying to predict the evolution of the surface concentration in the next decades, this amplitude is precious because it provides an evaluation of the range of uncertainty resulting from the unknown future state of the decadal oscillations (cf. Discussion section).

### 3.5. Regional Influences of the Climate Oscillations

In Equation (1), the collective influence of the de-trended climate indices is evaluated by the sum:

$$a_1NAO_{det} + a_2PDO_{det} + a_3AO_{det} + a_4ENSO_{det} + a_5EAWR_{det} + a_6IOD_{det} \quad (2)$$

This sum was calculated for each location, each month of the 1985–2020 period, and for both C50 and C90. The time series obtained in this way serves as a reference to which the results obtained in 10 different experiments can be compared. In experiments 1 to 4, only the terms corresponding to the NAO and AO, PDO and ENSO, EAWR, and IOD are taken into account (note that the NAO and AO, and the PDO and ENSO are considered together because of their close relationship, as evidenced in Section 3.1).

These first experiments allow for quantifying the individual importance of the NAO/AO, PDO/ENSO, EAWR, and IOD oscillations in the interpretation of the variability in the surface concentrations at a given location. In Experiments 5 to 10, the six possible choices of pairs of oscillations among the NAO/AO, PDO/ENSO, EAWR, and IOD are considered with the idea that a potential improvement in the results over those of Experiments 1 to 4 would highlight the interest of using combinations of oscillations rather than individual ones. Practically, an experiment is arbitrarily considered satisfactory if the comparison of its results with the reference time series yields an  $R^2 > 0.75$ .

Examination of the results from the 10 experiments performed on C50 (Table 3a) reveals that satisfactory ones are obtained at 7 locations when considering just one oscillation. This oscillation can be the NAO/AO (in Dakar and the Iran Desert), the PDO/ENSO (in El Fasher, Khartoum, and Saudi Arabia north), or EAWR (in Inner Mongolia and Kandahar). When combining two oscillations, the quality of the results improves at six of these seven locations (Inner Mongolia is the only exception) and becomes satisfactory at nine additional locations.

In all, 16 of the 18 initial locations meet the  $R^2$  criterion when using 1 or 2 oscillations. In some cases, it is easy to determine if one of the two oscillations plays a more important role than the other. For instance, in Khartoum,  $R^2 = 0.82$  when using just the PDO/ENSO, and it increases only slightly (to 0.88) with the help of the NAO/AO. In the Registan Desert (Kandahar), it can be concluded that the EAWR dominates neatly, as it did in Inner Mongolia, because adding the effect of the IOD is not strikingly beneficial for  $R^2$  (it increases from 0.81 to 0.88).

In El Fasher, the PDO/ENSO dominates from the start ( $R^2 = 0.78$ ), although adding the NAO/AO still significantly improves  $R^2$  (0.96). Nonetheless, there are cases for which the advantage of a combination of oscillations is even more obvious. In Cairo,  $R^2$  (0.64) was below the 0.75 limit with only the EAWR, and the addition of the effect of the IOD allows it to reach the level considered satisfactory.

**Table 3.** Coefficient of determination obtained when comparing the time series recalculated with just 1, or at most 2 oscillations, to the reference results yielded by Equation (2) with all the oscillations. Results are provided separately for C50 (a) and C90 (b).

| (a) |                  |          |            |      |     |                       |                   |                  |                     |                    |            |
|-----|------------------|----------|------------|------|-----|-----------------------|-------------------|------------------|---------------------|--------------------|------------|
| C50 | Location         | NAO + AO | PDO + ENSO | EAWR | IOD | (NAO/AO) + (PDO/ENSO) | (NAO + AO) + EAWR | (NAO + AO) + IOD | (PDO + ENSO) + EAWR | (PDO + ENSO) + IOD | EAWR + IOD |
|     | Western Sahara   | 5%       | 0%         | 48%  | 21% | 4%                    | 91%               | 7%               | 58%                 | 2%                 | 51%        |
|     | Dakar            | 79%      | 57%        | 6%   | 37% | 96%                   | 76%               | 83%              | 70%                 | 61%                | 21%        |
|     | Bamako           | 35%      | 21%        | 14%  | 61% | 41%                   | 65%               | 69%              | 22%                 | 64%                | 71%        |
|     | Niamey           | 0%       | 44%        | 0%   | 1%  | 56%                   | 0%                | 1%               | 48%                 | 79%                | 1%         |
|     | El Fasher        | 60%      | 78%        | 0%   | 33% | 96%                   | 37%               | 45%              | 88%                 | 75%                | 10%        |
|     | Khartoum         | 50%      | 82%        | 11%  | 11% | 88%                   | 29%               | 6%               | 81%                 | 85%                | 17%        |
|     | Somalia          | 1%       | 54%        | 60%  | 0%  | 66%                   | 33%               | 0%               | 68%                 | 85%                | 12%        |
|     | Libya (SE)       | 69%      | 62%        | 7%   | 6%  | 84%                   | 67%               | 50%              | 62%                 | 56%                | 7%         |
|     | Cairo            | 2%       | 1%         | 64%  | 28% | 4%                    | 59%               | 17%              | 70%                 | 17%                | 88%        |
|     | Libya (N)        | 25%      | 47%        | 38%  | 0%  | 48%                   | 63%               | 20%              | 61%                 | 70%                | 11%        |
|     | Saudi Arabia (N) | 40%      | 77%        | 40%  | 6%  | 81%                   | 61%               | 4%               | 88%                 | 88%                | 1%         |
|     | Iran Desert      | 83%      | 52%        | 1%   | 20% | 96%                   | 91%               | 81%              | 40%                 | 45%                | 4%         |
|     | Isfahan          | 42%      | 50%        | 24%  | 15% | 71%                   | 91%               | 43%              | 42%                 | 52%                | 26%        |
|     | Gobi             | 1%       | 10%        | 55%  | 31% | 16%                   | 80%               | 22%              | 44%                 | 75%                | 83%        |
|     | Inner Mongolia   | 26%      | 29%        | 79%  | 3%  | 57%                   | 68%               | 15%              | 58%                 | 65%                | 43%        |
|     | Kandahar         | 8%       | 8%         | 81%  | 15% | 22%                   | 85%               | 16%              | 63%                 | 54%                | 88%        |
|     | Thar             | 0%       | 2%         | 34%  | 42% | 0%                    | 43%               | 25%              | 37%                 | 40%                | 76%        |
| (b) |                  |          |            |      |     |                       |                   |                  |                     |                    |            |
| C90 | location         | NAO + AO | PDO + ENSO | EAWR | IOD | (NAO/AO) + (PDO/ENSO) | (NAO + AO) + EAWR | (NAO + AO) + IOD | (PDO + ENSO) + EAWR | (PDO + ENSO) + IOD | EAWR + IOD |
|     | Western Sahara   | 20%      | 39%        | 10%  | 4%  | 35%                   | 7%                | 8%               | 76%                 | 43%                | 2%         |
|     | Dakar            | 69%      | 32%        | 1%   | 0%  | 70%                   | 68%               | 71%              | 33%                 | 24%                | 0%         |
|     | Bamako           | 27%      | 11%        | 43%  | 10% | 27%                   | 57%               | 68%              | 42%                 | 19%                | 36%        |
|     | Niamey           | 41%      | 13%        | 4%   | 7%  | 59%                   | 39%               | 82%              | 7%                  | 15%                | 4%         |
|     | El Fasher        | 45%      | 2%         | 6%   | 15% | 27%                   | 55%               | 43%              | 0%                  | 0%                 | 18%        |
|     | Khartoum         | 19%      | 16%        | 55%  | 0%  | 36%                   | 85%               | 23%              | 59%                 | 8%                 | 49%        |
|     | Somalia          | 60%      | 32%        | 12%  | 0%  | 60%                   | 51%               | 60%              | 26%                 | 37%                | 0%         |
|     | Libya (SE)       | 54%      | 55%        | 0%   | 4%  | 86%                   | 61%               | 37%              | 51%                 | 58%                | 4%         |
|     | Cairo            | 2%       | 28%        | 53%  | 16% | 13%                   | 53%               | 1%               | 81%                 | 31%                | 63%        |
|     | Libya (N)        | 23%      | 12%        | 19%  | 10% | 26%                   | 52%               | 55%              | 27%                 | 29%                | 24%        |
|     | Saudi Arabia (N) | 46%      | 62%        | 61%  | 5%  | 71%                   | 86%               | 31%              | 89%                 | 71%                | 30%        |
|     | Iran Desert      | 83%      | 49%        | 5%   | 49% | 93%                   | 81%               | 93%              | 63%                 | 63%                | 46%        |
|     | Isfahan          | 14%      | 55%        | 55%  | 3%  | 36%                   | 96%               | 11%              | 73%                 | 61%                | 44%        |
|     | Gobi             | 45%      | 12%        | 36%  | 1%  | 94%                   | 45%               | 38%              | 12%                 | 19%                | 1%         |
|     | Inner Mongolia   | 28%      | 28%        | 92%  | 0%  | 72%                   | 89%               | 22%              | 89%                 | 33%                | 89%        |
|     | Kandahar         | 24%      | 10%        | 84%  | 8%  | 58%                   | 91%               | 22%              | 64%                 | 43%                | 87%        |
|     | Thar             | 2%       | 12%        | 7%   | 1%  | 14%                   | 17%               | 2%               | 30%                 | 25%                | 7%         |

This is also the case of Western Sahara, where  $R^2$  increases from 0.48, with the EAWR alone, to 0.91 when adding the NAO/AO. Interestingly, the fact that, at the same location,  $R^2$  was only 0.05 for the NAO/AO emphasizes again that the effects of the oscillations are not simply additive. This is due to the fact that the de-trended oscillations are not necessarily in phase (cf., Section 3.1). It even occurs that combining an oscillation with another degrades the agreement (e.g.,  $R^2$  drops from 0.79 to 0.68 in Inner Mongolia when adding the NAO/AO to the EAWR).

Finally, in Bamako and Libya (North), using one or two oscillations is not enough for  $R^2$  to reach the 0.75 level. These locations are actually under the influence of at least three different oscillations. Calculations (not presented in Table 3) show that the best combinations are [NAO/AO; EAWR; IOD] for Bamako ( $R^2 = 0.99$ ), and [NAO/AO; PDO/ENSO; IOD] for north Libya ( $R^2 = 0.88$ ).

A similar analysis was performed with C90 (Table 3b). At El Fasher and in the Thar Desert, satisfactory results are obtained only when combining the four oscillations, but elsewhere, two or three of them are enough. In the most intricate cases, the degradation of the coefficient of determination observed when deleting successively each one of the four terms of Equation (2) was used to classify the oscillations by order of influence. The results (Table 4) show that the dominant oscillation depends on the region, but this is always either

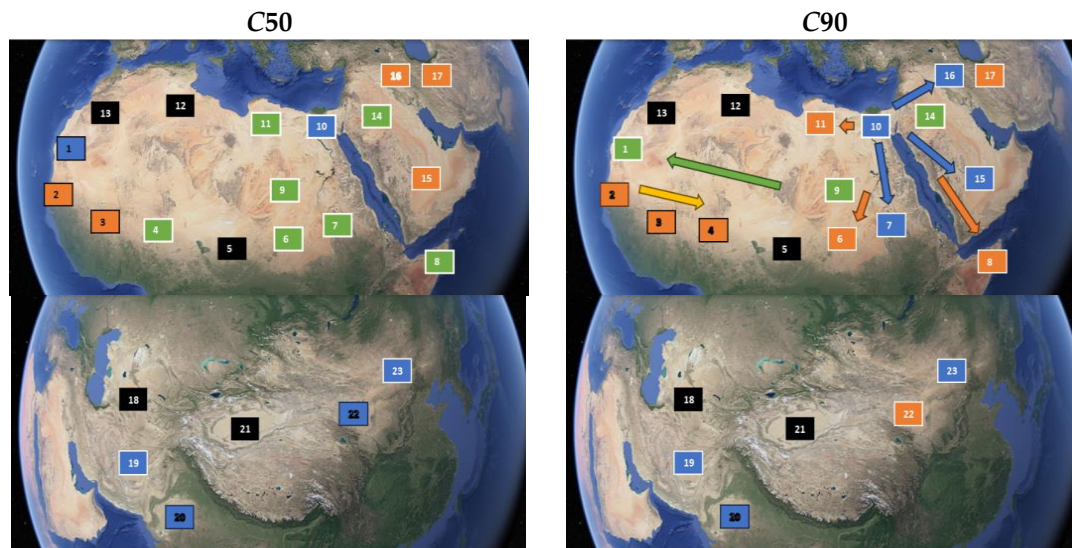
the NAO/AO, the PDO/ENSO, or the EAWR. When involved, the IOD comes, at best, in second position.

**Table 4.** Classification of the oscillations by order of influence on C50 (a) and C90 (b) in the different regions of the Dust Belt.

| (a) |                       |          |            |      |     |
|-----|-----------------------|----------|------------|------|-----|
| C50 | Location              | NAO + AO | PDO + ENSO | EAWR | IOD |
| 1   | Western Sahara        | 2        |            | 1    |     |
| 2   | Dakar                 | 1        | 2          |      |     |
| 3   | Bamako                | 1        | 2          | 3    |     |
| 4   | Niamey                |          | 1          |      | 2   |
| 6   | El Fasher             | 2        | 1          |      |     |
| 7   | Khartoum              | 2        | 1          |      |     |
| 8   | Somalia               |          | 1          |      | 2   |
| 9   | Libya (SE)            | 2        | 1          |      |     |
| 10  | Cairo                 |          |            | 1    | 2   |
| 11  | Libya (N)             | 3        | 1          |      | 2   |
| 14  | Saudi Arabia (N)      |          | 1          |      | 2   |
| 15  | Saudi Arabia (S)      | 1        |            | 2    |     |
| 16  | Isfahan               | 1        |            | 2    |     |
| 17  | Iran Desert           | 1        | 2          |      |     |
| 19  | Kandahar              |          |            | 1    | 2   |
| 20  | Thar                  |          |            | 1    | 2   |
| 22  | Gobi                  |          |            | 1    | 2   |
| 23  | Inner Mongolia        |          |            | 1    |     |
| (b) |                       |          |            |      |     |
| C90 | location              | NAO + AO | PDO + ENSO | EAWR | IOD |
| 1   | Western Sahara        |          | 1          | 2    |     |
| 2   | Dakar                 | 1        | 2          |      | 3   |
| 3   | Bamako                | 1        |            | 3    | 2   |
| 4   | Niamey                | 1        |            |      | 2   |
| 6   | El Fasher             | 1        | 3          | 2    | 4   |
| 7   | Khartoum              | 2        |            | 1    |     |
| 8   | Somalia               | 1        | 2          |      | 3   |
| 9   | Libya (SE)            | 2        | 1          |      |     |
| 10  | Cairo                 |          | 2          | 1    |     |
| 11  | Libya (N)             | 1        |            | 3    | 2   |
| 14  | Saudi Arabia (N)      |          | 1          | 2    |     |
| 15  | Saudi Arabia (S)      | 2        |            | 1    |     |
| 16  | Isfahan               | 2        |            | 1    |     |
| 17  | Iran Desert           | 1        | 2          |      |     |
| 19  | <b>Kandahar</b>       | 2        |            | 1    |     |
| 20  | <b>Thar</b>           | 4        | 1          | 2    | 3   |
| 22  | <b>Gobi</b>           | 1        | 2          |      |     |
| 23  | <b>Inner Mongolia</b> |          |            | 1    |     |

The locations where the NAO/AO, PDO/ENSO, and EAWR play the first role can be reported on a map (Figure 10). Note that depending on the sign of the sensitivity to a given oscillation, the color code used to represent it is different. This mapping reveals clear regional trends. Considering first C50 (left column on Figure 10), it can be seen that the western part of the Sahel is primarily sensitive (positive correlation) to the NAO/AO. When moving from there towards the east and northeast of Africa, and beyond that towards the north of the Arabian Peninsula, the PDO/ENSO takes over (negative correlation). The only

exception is Cairo, where the EAWR is the main factor of influence (negative correlation). This contrasts with Western Sahara, where the EAWR also dominates, but with a positive correlation with C50. In Iran and the south of the Arabian Peninsula, the NAO/AO prevails (negative correlation). Finally, the EAWR plays again the leading role in the rest of Asia, and the sign of the correlation can be either positive (Thar and Gobi) or negative (Kandahar and Inner Mongolia).



**Figure 10.** Mapping of areas where C50 (left column) and C90 (right column) are primarily influenced by the NAO/AO (orange color), PDO/ENSO (green color), and EAWR (blue color) oscillations. The white (black) numbers and frames indicate a negative (positive) correlation.

When considering C90 (right column of Figure 10), the zone of positive influence of the NAO/AO in the western Sahel is seen to expand towards the east at the expense of the PDO/ENSO. The same is observed as regards the NAO/AO area of negative influence: it was originally limited to Iran and the south of Saudi Arabia, but progresses towards the east and northeast of Africa. Within this vast region, the EAWR nucleus also extends its influence towards the south (Sudan), southeast (South of Saudi Arabia), and the east (West of Iran). In East Asia, the only difference as regards C50 is in Gobi, where the NAO/AO has a larger influence on C90 than the EAWR.

These comparisons show that the oscillation with the largest influence on the dust concentration not only depends on the region but also on the type of concentration considered. For instance, in Khartoum, the PDO/ENSO and the NAO/AO control the variability in the mean (C50) dust concentration, but the extreme concentrations (C90) are sensitive in the first place to the EAWR, then to the NAO/AO. Similarly, in the horn of Africa (Somalia) C50 is controlled by the PDO/ENSO and the IOD, but for C90, it is NAO/AO that assumes the main role before the PDO/ENSO and the IOD.

#### 4. Discussion

This work analyzed the statistical correlation between the surface (mean and extreme) concentrations in the whole Dust Belt and climate oscillations. Only the decadal temporal scales were considered, which excludes the analysis of the higher-frequency (seasonal and interannual) variability. A parameterization assuming that the variations in the surface concentrations were essentially controlled by climate conditions, and that the effects of the external (anthropogenic) and internal forcings could be separated was proposed. This parameterization was validated by the comparison of the reconstructed and observed time series of surface dust average and extreme concentrations. Although the model did not

include lag-memory or threshold effects, it was found to describe well the concentration variations at 18 of the 23 locations selected to represent the diversity of conditions in the Dust Belt. This good performance is most probably attributable in part to the averaging over periods of 10 years.

In the western part of the Sahel, both C50 and C90 have been decreasing between 1985 and 2020, and after removal of the temporal trend, it was found that they were primarily, and positively, correlated with the decadal variations in the NAO/AO. Between 1990 and 2005, the NAO shifted from a positive to a negative phase (cf. Figure 3), which led to an increase in the precipitations because of the negative correlation between rainfall in the Sahel and the oscillation [67]. This could explain, at least in part, the greening of the Sahel (e.g., [68]) and the decrease in dust concentration.

However, this idea of a “recovering” of the Sahel after the dramatic drought of the 1970s and 1980s has been debated because it seemed to be limited to its western part. For instance, Elagib and Elhag [69] analyzed the measurements of meteorological stations in Sudan and showed that, since the 1940s, a significant decline in rainfall combined with a drastic increase in temperature variables favoring evapotranspiration has occurred over the northern half of the country.

This slow and progressive shift is most probably attributed to anthropic activities and the ensuing climate change. However, these intensifying drought conditions were particularly severe around 1970 and 2010, in good temporal coincidence with negative phases of the PDO/ENSO. All these observations are consistent with our results, evidencing the predominant impact of the PDO/ENSO oscillation on the fluctuations in the average dust concentration, not only in Sudan, but more generally in East/Northeast Africa, and in the Arabian Peninsula.

Our analysis also showed that most regions of the Dust Belt are under the influence of at least two different oscillations. In this case, the oscillation with the largest influence on C50 is not necessarily the same as that controlling C90. This explains that the temporal patterns of the average and extreme concentrations at a given location might be out of step, as was observed in large sections of northeastern Africa and the Arabian Peninsula. Basically, this is due to the fact that the zones in which the NAO/AO (and EAWR) dominates, the variations in C90 are larger than those where they control C50.

Three of the five sites where the parameterization failed to represent the variations in both C50 and C90 are at the frontier between the areas controlled by two or three different oscillations. This is the case of Tindouf, Niamey, and the Great Western Sand Sea, which are located between West Africa, where the NAO/AO or the EAWR dominates, and the eastern part of the continent, where the PDO/ENSO or the EAWR dominates.

In Asia, the reasons why the parameterization failed in Turkmenistan and Taklamakan are unclear. In the latter case, it is possible that the correlation between dust concentration and climate oscillations was weakened by the implementation of the Great Green Wall, an afforestation project started in 1978, completed in 2024, and whose purpose was to stop the progression of the desert [70].

Regarding this influence of anthropogenic activities on wind erosion, two different mechanisms can be theoretically distinguished. The first one is a consequence of the fact that the warming occurring at a global scale affects the temperature, wind regime, precipitation, evapotranspiration, and vegetation of each region of the world in different manners. As a result of all these, assumedly slow modifications in environmental factors, such as wind erosion, can either be facilitated, hindered, or left unchanged.

In addition, the potential impact of more regional human activities on wind erosion also needs to be taken into account in some regions. Under the pressure of an exponential population growth, ill-adapted agricultural and pastoral practices may have led to land

degradation and increased wind erosion in the Sahel (e.g., [71]), but some authors also underline the farmers' ability to adapt to new ecological and economical constraints [72].

The sign and magnitude of parameter  $\alpha$  in Equation (1) do not distinguish between these two mechanisms and only reflect the efficiency of their combination. Despite this limitation,  $\alpha$  is a more robust indicator of the sensitivity of a region to human activities than the slopes (Sl.  $C_{50}$  and Sl.  $C_{90}$ ) of the time series of observed concentrations.

The case of  $C_{90}$  in Inner Mongolia is a good example to illustrate this difference. The  $\alpha$  reported in Table 2 ( $-11.7\%/decade$ ) suggests a much faster decrease between 1985 and 2020 than the Sl.  $C_{90}$  ( $-1.7\%/decade$ ) calculated using the observations (Table 1). This is due to a partial compensation effect resulting from the fact that (1) the EAWR index decreased in this period (cf. Figure 3), and (2)  $C_{90}$  is strongly and negatively correlated with EAWR in this region (Table 2 and Figure 10).

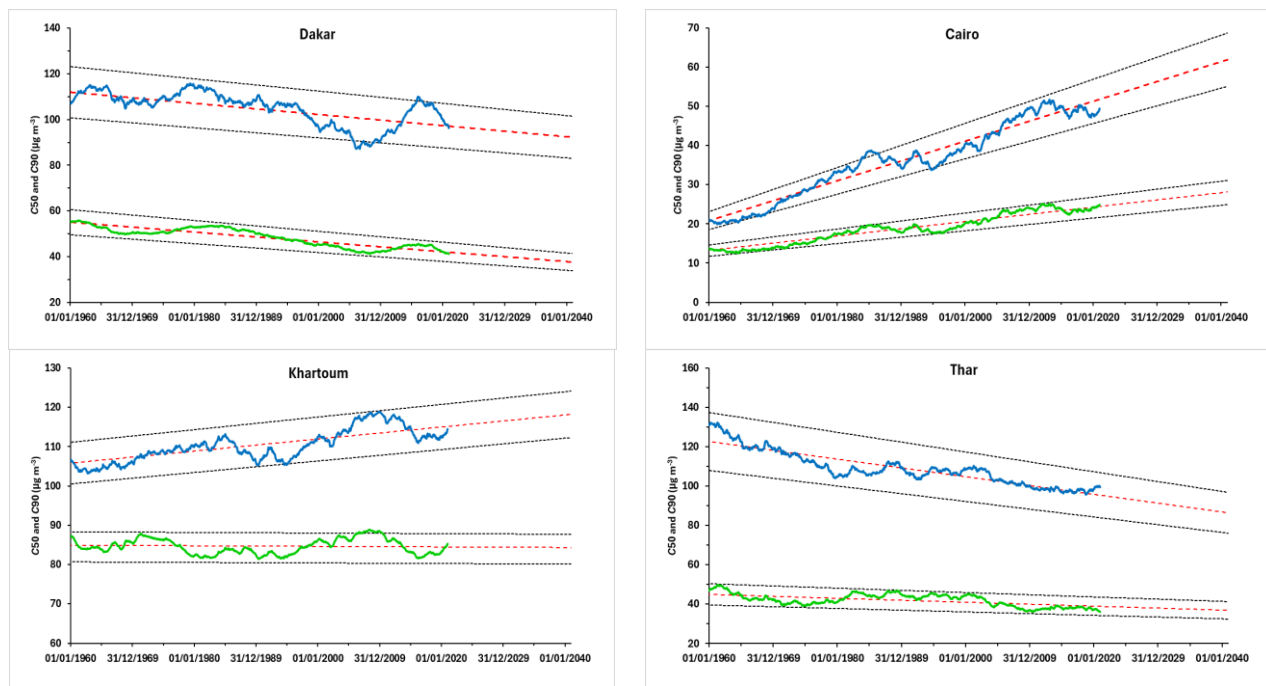
As a result of this discussion, it appears that the projections made to predict the evolution of dust concentration in the next decades should be primarily based on  $\alpha$  rather than on a simple extrapolation of the observations made during a necessarily limited period. In these projections, a first source of uncertainties arises from the unpredictable character of the internal variability in the climate system.

However, the analysis presented in Section 3.4 suggests that these uncertainties should rarely exceed 10% of the values obtained by extrapolating the temporal trend of the current period. For the reconstruction of the evolutions of  $C_{50}$  and  $C_{90}$  in the decades preceding the satellite era (1980s onward), things are much simpler because long time series of past climate indices are available. The second source of uncertainty for the future projections lies in the value of  $\alpha$  itself.

The pace at which our climate is changing is not constant, but rather accelerating [73]. This means that  $\alpha$  tends to evolve with time over the long term. Furthermore, the adaptation measures taken by the populations to counteract the adverse effects of the changing climate would also modify  $\alpha$  but rather progressively because changing secular practices takes time. In summary, the value of  $\alpha$  deduced from the analysis of the 1980–2025 data can be used for extrapolation purposes over durations limited to one or two decades in the past or the future. Therefore, we reconstructed the variations in the concentrations in the 1960–2040 period.

Examples of such concentration evolutions are presented in Figure 11 for three major cities (Cairo, Dakar, and Khartoum) of the Dust Belt, and for the Thar Desert, under the wind of which lies the north of India. In Dakar and Khartoum, both  $C_{50}$  and  $C_{90}$  were extremely large in 1960. They are decreasing in Dakar but too slowly to stop constituting a health problem in 2040 ( $C_{50}$  ca.  $38 \mu\text{g m}^{-3}$ ). The amplitude of the oscillations resulting from the internal variability in the climate system is about 10% for  $C_{50}$  and  $C_{90}$ .

In Khartoum,  $C_{50}$  oscillates (amplitude ca. 5%) around a very high but stable level ( $85 \mu\text{g m}^{-3}$ ), but  $C_{90}$  will continue to increase and be close to  $120 (\pm 5\%) \mu\text{g m}^{-3}$  in 2050. In Cairo,  $C_{50}$  will have more than doubled between 1960 and 2040 (13 and  $28 \mu\text{g m}^{-3}$ , respectively), and  $C_{90}$  trebled (from 20 to  $61 \mu\text{g m}^{-3}$ ). Unfortunately, this means that in these three densely populated regions, it would be unrealistic to hope to rapidly bring the  $\text{PM}_{2.5}$  concentration below the  $5 \mu\text{g m}^{-3}$  level recommended by the WHO. In the Thar Desert, the extreme and mean dust concentrations have been decreasing [74] and they are expected to continue doing so. Between 1960 and 2040,  $C_{90}$  will have receded from 120 to  $86 (\pm 12\%) \mu\text{g m}^{-3}$  and  $C_{50}$  from 48 to  $37 (\pm 12\%) \mu\text{g m}^{-3}$ , which is still high and will continue to contribute to the degradation of the air quality in the north of India.



**Figure 11.** Reconstruction of the time series of mean (C50, green line) and extreme (C90, blue line) PM2.5 dust concentration at 4 locations of the Dust Belt. The projections up to 2040 (red dotted lines) and the limits of uncertainties (black dotted lines) are also indicated.

## 5. Conclusions

Our analysis of data from the 1980–2025 period showed that the dust emission trends in the Dust Belt are not homogeneous. At the decadal timescales, the recent evolution of wind erosion in its sub-regions can be represented by a linear temporal trend (of slope  $\alpha$ ) modulated by the effects of the internal variability in the climate system. The trajectory of dust emissions in the next decades primarily depends on the sign and magnitude of  $\alpha$ , two characteristics that reflect the sensitivity of dust emissions to human activities. In desert areas, it is solely controlled by the effects of the global climate change (soil and air temperatures, precipitation, wind characteristics, etc.), but in semi-arid regions, other human actions (agricultural practices, water management, etc.) may also influence it. In this more complex case, further studies aiming at disentangling the exact roles of global change and regional factors would be necessary to propose mitigation strategies.

In some sub-regions of the Dust Belt, dust emissions have been globally tending to recede over the last few decades, and they should continue to do so in the next few decades. This is the case of the western part of the Sahel and of some Asian semi-arid areas (e.g., Inner Mongolia) where the influence of the NAO/AO and EAWR, respectively, has led to variations in the surface concentrations but not sufficient to curb the global decreasing trend. Conversely, emissions are rapidly increasing in East and Northeast Africa, and particularly along the southern shore of the eastern Mediterranean basin, a region known to be a hot spot of sensitivity to the ongoing climate change [75]. In Cairo, the decadal mean of the dust concentration (C50) is expected to have more than doubled between 1960 and 2040. Interestingly, the 90th percentile of the dust concentration (C90) should have tripled in the same period. This is consistent with the modeling of the future climate of Egypt, showing that the probability of occurrence of extreme events will increase faster than the mean temperature [76].

Even where emissions are decreasing, concentrations can remain at a very high level. This is the case of the western part of the Sahel, where the modulation of the regional

climate by the NAO/AO has led to dramatic consequences for the local populations and for the environment. Drought, famine, and extreme dust concentration episodes of recent history can in large part be explained by these fluctuations. Obviously, the implications of the internal (supposedly natural) variability in the climate system are even more important in regions where the trend is of an increase in drought conditions and dust emissions. The recurrent famines of East Africa can be linked to fluctuations in the PDO/ENSO. However, most sub-regions of the Dust Belt are not under the influence of a single but of two or even three climate oscillations. Our results showed that the effects of the NAO/AO, PDO/ENSO, EAWR, and IOD needed to be combined to fully explain the variability in surface concentrations.

**Supplementary Materials:** The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/earth7040110/s1>. Figure S1: Comparison of the time series of surface dust concentration in Cairo yielded by the MERRA-2 and CAMS reanalyses (note that the ranges of dust particle diameters are different for the two reanalyses). Figure S2: Correlation between the dust-PM<sub>2.5</sub> concentrations estimated by MERRA-2 and the dust-PM<sub>0.9</sub> and dust-PM<sub>20</sub> estimated by CAMS. The case displayed is that of Cairo, and the data used are monthly averages of the 2003–2025 period.

**Author Contributions:** Conceptualization and methodology, M.E.-N., A.W. and S.C.A.; validation, A.M., M.H.E. and G.S.; formal analysis, M.E.-N.; writing—original draft preparation, M.E.-N., A.W., A.M. and M.H.E.; writing—review and editing, S.C.A.; supervision, M.M.A.W. and S.C.A. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** All the datasets used in this work are available in public archives whose details are given in the text of this manuscript.

**Acknowledgments:** The authors thank NASA's GIOVANNI online data system, developed and maintained by the NASA GES DISC, for facilitating access to the MERRA-2 products. Copernicus Atmosphere Monitoring Service (CAMS) data were also used in this study, and we acknowledge the European Centre for Medium-Range Weather Forecasts (ECMWF) for providing these resources.

**Conflicts of Interest:** The authors declare no conflicts of interest.

## Abbreviations

The following abbreviations are used in this manuscript:

|         |                                               |
|---------|-----------------------------------------------|
| AERONET | Aerosol Robotics Network                      |
| MODIS   | Moderate-Resolution Imaging Spectroradiometer |
| AVHRR   | Advanced Very-High-Resolution Radiometer      |
| MISR    | Multi-angle Imaging SpectroRadiometer         |

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