EVALUATION OF THE DUST FORECASTS IN THE CANARY ISLANDS

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Summary

Mineral dust predictions from a number of operational and research centres around the world are daily exchanged in the framework of the WMO Sand and Dust Storm - Warning Advisory and Assessment System (SDS-WAS). Moreover, the SDS-WAS Regional Center for Northern Africa, Middle East and Europe daily computes the multi-model median. Forecasts of dust optical depth (DOD) are routinely evaluated with sun-photometric (AERONET) and satellite (MODIS) aerosol products. However, there is not a systematic evaluation of dust surface concentration (DSC). In the present work, forecasts of DSC released by seven models are compared with PM10 observations (particulate matter with aerodynamic diameter less than 10 µm) recorded by the Air Quality Control and Monitoring Network of the Canary Islands (Spain). Since PM10 measurements integrate particles of different origin, including anthropogenic and natural aerosols, the contribution of mineral dust to the total PM10 is estimated using two different methods. Complementarily, aerosol optical depth (AOD) from the AERONET station of Santa Cruz de Tenerife is compared with DOD simulated by the models. Different approaches are tested to consider only the contribution of dust to the total value of AOD in the AERONET retrievals.

Contents

1. Introduction

Over the last years, the scientific community has begun to realize the important impacts of airborne dust on weather and climate, human health, the environment and various socio-economic sectors. Numerical prediction of mineral dust has become prominent at a number of research centers and operational meteorological institutes due to growing interest from diverse stakeholders, such as air quality and health professionals, aviation authorities, solar power plant managers and policymakers.

The most relevant variables provided by dust prediction models are dust load, or alternatively dust optical depth (DOD), as a measure of the total dust contents in an atmospheric column and dust surface concentration (DSC), as a measure of the dust contents near the ground. Other variables that are relevant for specific applications are dry and wet deposition or surface extinction.

An exhaustive evaluation of the products derived from numerical models is imperative before their practical application. The main goal of such evaluation is to quantitatively and qualitatively assess whether the modeling system is successfully predicting the temporal and spatial distribution of the different parameters. Forecast evaluation also allows exploring the adequacy and correctness of the science represented in the model for the purposes for which the model is applied and, therefore, evaluation results should lead to new directions in model development and improvement (Benedetti et al., 2014).

The first problem of the forecast evaluation is the scarcity of suitable in-situ measurements, especially close of the main dust sources. The first option is the use of satellite products. However, satellite measurements are integrated over the atmospheric column and also over the different aerosol species. Another option is the use of ground-based photometric retrievals, but they present a similar problem. Initiatives to establish routine evaluation of dust predictions have been mainly focused on total-column DOD. In particular, the Regional Center for Northern Africa, Middle East and Europe of the World Meteorological Organization's Sand and Dust Storm - Warning Advisory and Assessment System (WMO SDS-WAS) has set up and maintains a joint visualization and forecast evaluation (Terradellas et al., 2016), which currently involves 12 modeling systems and is based on AERONET (Holben et al., 1998; Dubovik and King, 2000) and MODIS retrievals (Levy et al., 2013). Other initiatives have been conducted in the framework of AeroCom (Huneeus et al., 2011), the Copernicus Atmosphere Monitoring Service (CAMS) (Eskes et al., 2015; Cuevas et al., 2015) and the International Cooperative for Aerosol Prediction (ICAP) (Sessions et al., 2015).

Many user communities are interested in the concentration near the surface (in the air we breathe) rather than in the total column content. Therefore, evaluation of the predicted DSC is also necessary. Air quality monitoring networks are the main data providers for this purpose.

They are common and with high spatial density in Europe, but very sparse and discontinuous close of the main source regions. The lack of observational data is particularly acute near the Sahara, the major dust source on Earth (Middleton and Goudie, 2001).

The evaluation of dust forecasts using PM10 data has some drawbacks. On the one hand, the values of PM10 do not only reflect the mineral dust content in the atmosphere, but integrate the contribution of all airborne particles with aerodynamic diameter less than 10 µm, which may be of diverse origins (mineral dust, marine aerosol, anthropic pollution, etc.). On the other hand, dust prediction models provide the total content of mineral dust and, at least some of them, consider particles larger than 10 µm.

To quantify the contribution of mineral dust to PM10, the most reliable method is based on the chemical analysis of filters from gravimetric samplers (Rodrıguez et al., 2012). However, this is a very expensive and laborious technique, so it is difficult to apply routinely. As an alternative, the present work tests an approach based on the subtraction of a background level from the PM10 measurements. This background level is computed after the application of a monthly moving percentile to the PM10 time series, following Escudero et al. (2007). The use of the coarse fraction of PM, defined as the difference PM10-PM2.5, as a proxy of the dust concentration is also tested.

The evaluation is conducted for the Canary Islands. The archipelago suffers frequent intrusions of dust from the Sahara (i. e. Middleton and Goudie, 2001; Basart et al., 2009), with significant negative impacts, especially on air quality and health (Viana et al., 2002). Therefore, there is great interest in learning how the dust prediction models behave in the region. However, the complex orography of the islands, imperfectly represented in the models, especially in those with lower resolution, prevents a good simulation of the local variations of dust concentration and makes difficult a correct evaluation of the forecasts.

This analysis is complemented with the evaluation of DOD forecasts with retrievals of total aerosol optical depth (AOD) from the AERONET station of Santa Cruz de Tenerife. As with PM measurements, it is necessary to take into account the contribution of particles other than mineral dust to the total AOD. First, the same method as in SDS-WAS is applied. It consists of restricting the comparison to situations in which mineral dust is the dominant aerosol type. For that, threshold discrimination is made and observations with an Angstrom Exponent 440-870 ($AE_{440-870}$) higher than 0.6 are discarded (Terradellas et al., 2016). Then, three alternative methods have been tested and their respective results discussed and compared.

2. Geographical framework

The Canary Islands are located in the sub-tropical Northern Atlantic, roughly 100 km west of the Moroccan coast (figure 1), and are often affected by intrusions of Saharan dust. Quasi-permanent subsidence in the free troposphere together with frequent trade winds in the lowest troposphere, especially during summer, result in a strong and stable thermal inversion (located on average at 1400 m a.s.l) that separates a dry free troposphere from a relatively fresh and humid oceanic boundary layer (Torres et al., 2002). From autumn to spring, frequent low-altitude Saharan dust outbreaks (< 1000 m a.s.l) are observed. Conversely, long-range dust transport above the trade wind inversion layer (> 1500m a.s.l) is sometimes observed from early summer to early-autumn (Viana et al., 2002; Querol et al., 2004; Alonso-Pérez et al., 2007).

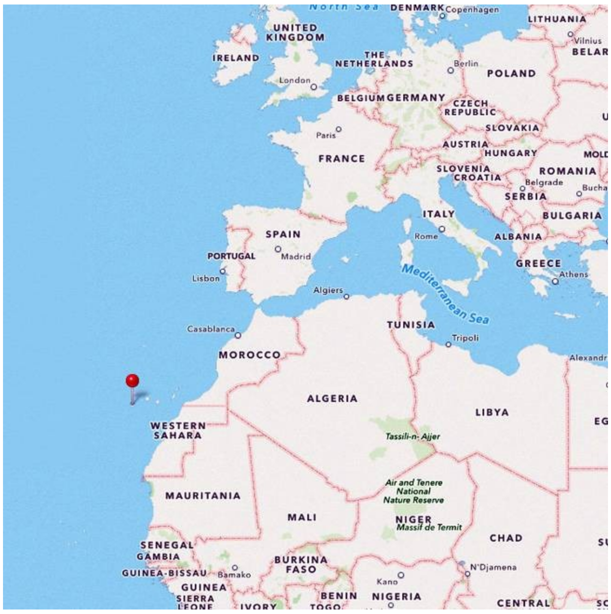

Figure 1: Geographical situation of the Canary Islands (red pin)

3. Materials and Methods

3.1. Forecast Models

Daily predictions of DOD and DSC released by seven different dust prediction models for the period 2013-2015 are considered in this work. The models have very different characteristics. There are global and limited-area models. Some of them incorporate schemes of data assimilation, others do not. Their horizontal and vertical resolutions are diverse, as well as their meteorological drivers, parameterisation of the different steps of the dust cycle and physiographical databases of land use, soil texture, etc. The list of the models and their main characteristics are summarized in table 1.

Model	Institution	Meteorological driver	Domain	Data assimilation
BSC-DREAM8b	Barcelona Supercomputing Center	Eta-NCEP	Regional	No
CAMS	ECMWF	IFS-ECMWF	Global	MODIS AOD
DREAM8-NMME-MACC	SEEVCCC	NMME-NCEP	Regional	CAMS analysis
MetUM	Met Office	MetUM	Global	MODIS AOD
NMMB/BSC-Dust	Barcelona Supercomputing Center	NMMB-NCEP	Regional	No
GEOS-5	NASA	GEOS-5	Global	MODIS
NGAC	NCEP	NEMS-GFS	Global	No

Table 1: Dust models involved in the study

Although predictions are available up to 72 hours, three-hourly predictions from 3 to 24 hours are considered in the evaluation. The study of the degradation of the prediction with the lead time is outside the scope of this work.

3.2. Ensemble Products

Ensemble prediction aims to describe the future state of the atmosphere from a probabilistic point of view. Multiple simulations are run to account for the uncertainty of the initial state and/or for the inaccuracy of the model and the mathematical methods used to solve its equations (Palmer et al., 2005). Multi-model ensembles also represent a paradigm shift in which offering the best product to the users as a collective scientific community becomes more important than competing for achieving the best forecast as individual centres (Benedetti et al., 2014).

Multi-model products are generated from the output files provided by the dust prediction models listed in table 1, using the so-called poor man approach (Atger, 1999). Centrality products (median and mean) aim at improving the forecasting skill of the single-model approach. Spread products (standard deviation and range of variation) indicate whether the forecast fields are consistent within the contributing models, in which case there is greater confidence in the forecast (Terradellas et al., 2016). The SDS-WAS multi-model median has been added to the collection of individual models for evaluation.

3.3. Data from Air Quality Monitoring Stations

The nine stations from the Canarian Air Quality Monitoring Network, operated by the regional government, that are listed in table 2 have been chosen for the present study. As far as possible, the selection includes stations located away from urban centers, industrial parks and roads so that the contribution of anthropogenic particles in their records be small. Also, it has been intended that the location of the selected stations be representative of the different geographical areas of the archipelago, as shown in figure 2.

Number	Site	Location	Method	Parameters
1	Costa Teguise	Lanzarote	TEOM	PM10 and PM2.5
2	Tefía - Puerto del Rosario	Fuerteventura	Beta attenuation	PM10
3	Polideportivo Afonso - Arucas	Gran Canaria (N)	Beta attenuation	PM10 and PM2.5
4	Camping Temisas - Sta Lucía de Tirajana	Gran Canaria (S)	TEOM	PM10 and PM2.5
5	Granadilla	Tenerife (S)	Scattering	PM10 and PM2.5
6	Vuelta Los Pájaros - Santa Cruz de Tenerife	Tenerife (N)	Beta attenuation	PM10 and PM2.5
7	Residencia Escolar - San Sebastián de la Gomera	La Gomera	Beta attenuation	PM10
8	Las Balsas - San Andrés y Sauces	La Palma	Beta attenuation	PM10
9	Echedo - Valverde	El Hierro	Beta attenuation	PM10

Table 2: Air quality monitoring stations used in the study

Different continuous particle samplers are used in the Canarian network. They measure inertial mass (Tapered Element Oscillating Microbalance, TEOM), electron attenuation (Beta attenuation) or light scattering (scattering) of fine particles at a sampling rate of 1 hour. The reference (gravimetric) method to measure PM10 and PM2.5 consists of acquiring deposits over 24-hour periods on teflon membrane filters from air drawn at a controlled flow rate through the corresponding inlet. Then, a correction factor obtained through sampling campaigns has to be introduced to adjust the results to the reference method. The data used in the present study, from 2013 to 2015, had already been corrected by the network managers.

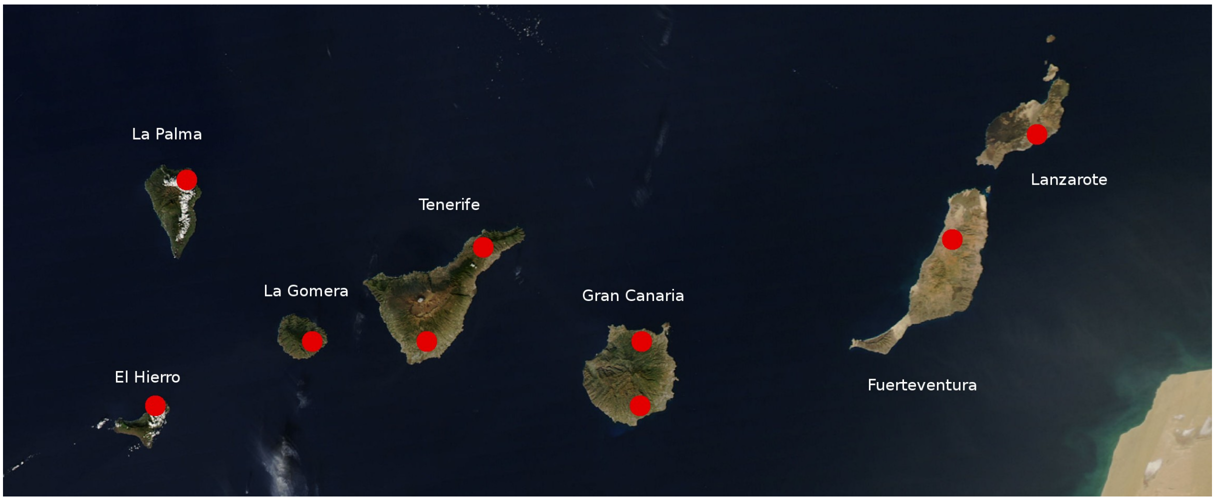

Figure 2: Location of the stations

3.4. Data from AERONET

AERONET level 1.5 version 3 inversion products from the station of Santa Cruz de Tenerife have been used for the present study. Level 1.5 data are cloud-screened, but the calibration correction has not been applied. In particular, the following parameters have been considered: AOD, $AE_{440\text{-}870}$ and coarse-mode AOD.

Since AERONET does not yield AOD at 550 nm, which is the wavelength considered for models, this variable is calculated from the AOD at 440, 675 and 870 nm and the $AE_{440\text{-}870}$ using the Angström law.

Rather than time-interpolated, AERONET-derived data are assigned to the nearest multiple-of-3 hour. In case more than one observation is assigned to the same hour, only the closest-in-time is considered.

3.5. Estimation of the dust contribution to PM measurements

Three different methods have been tested to assess the contribution of mineral dust to three-hourly PM10 measurements. The first method is based on Escudero et al. (2007), although with several modifications. It is referred in this report as Perc40 and is based on the subtraction of a background level (BL) from the three-hourly PM10 time series. To compute this BL, measurements from dusty days, identified from records of the Spanish Ministry of Agriculture, Food and Environment, are removed from the series. Then, at each time step, the BL is the 40th percentile of a mobile one-month subset of measurements around it.

The second method, referred here as PMcoarse, is conceptually much more simple and consists of considering the coarse fraction of PM10, that is, the value PM10 – PM2.5 as the contribution of mineral dust to PM10 measurements. This method, obviously, can only be applied to those stations that provide PM2.5 measurements (see table 2).

Finally, the third method (referred as NoFilter) consists of directly using PM10 to compare with model-derived DSC in the forecast evaluation.

3.6. Estimation of the dust contribution to AOD

As in PM measurements, AERONET AOD retrievals integrate the contribution of different aerosol species. Four strategies have been tested to minimize the sources of error in the evaluation.

The first method (referred here as Filter06) intends to restrict the comparison to situations in which mineral dust is the dominant aerosol type. This is done through threshold discrimination. It is assumed that when the $AE_{440-870}$ is above 0.6, there is a large abundance of fine particles (Pérez et al., 2006) and the corresponding AOD value will not be considered for forecast evaluation

The second method (referred as Filter06_12) is similar to the previous one. However, here the evaluation is extended to cases in which we consider there is no mineral dust at all. It is assumed that when the $AE_{440-870}$ is above 1.2, there are almost no coarse particles and the corresponding AOD value is set to 0. So, only those cases with an $AE_{440-870}$ between 0.6 and 1.2 are excluded.

The third method (referred as Coarse) makes use of the spectral de-convolution algorithm described in O'Neill et al. (2003) that is part of the AERONET routine calculations. This algorithm yields fine (sub-micron) and coarse (super-micron) AODs at a standard wavelength of 500 nm. The Coarse method consists of assuming that the coarse AOD is the dust contribution to the total AOD. In this case, all measurements are used in the evaluation.

Finally, the forth method (referred as NoFilter) consists of directly using the AERONET AOD retrievals without any filter to compare with model-derived DOD in the forecast evaluation.

3.7. Evaluation scores

The common metrics used to quantify the departure between simulated and observed quantities are listed in table 3.

Statistic Parameter	Formula	Range	Perfect score
Mean Bias Error (BE)	$BE=\frac{1}{n}\sum_{i=1}^{n}(c_i-o_i)$	$-\infty$ to $+\infty$	0
Root Mean Square Error (RMSE)	$RMSE=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(c_i-o_i)^2}$	0 to $+\infty$	0
Correlation coefficient (r)	$r=\frac{\sum_{i=1}^{n}(c_i-\bar{c})\cdot(o_i-\bar{o})}{\sqrt{\sum_{i=1}^{n}(c_i-\bar{c})^2}\cdot\sqrt{\sum_{i=1}^{n}(o_i-\bar{o})^2}}$	-1 to 1	1
Fractional Gross Error (FGE)	$FGE=\frac{2}{n}\sum_{i=1}^{n}\left\lvert\frac{c_i-o_i}{c_i+o_i}\right\rvert$	0 to 2	0

Table 3: Metrics used in the evaluation: c_i are simulated values, o_i observed values and n number of values

The mean Bias Error (BE) captures the average deviation between two datasets. It has the same units as the variable being evaluated. Negative values indicate underestimation and positive values indicate overestimation of the model. The Root Mean Square Error (RMSE) combines the bias and the standard deviation. It is strongly dominated by the largest values, due to squaring. Especially in cases where prominent outliers occur, the usefulness of RMSE is questionable and its interpretation becomes difficult. The correlation coefficient (r) indicates the extent to which spatial and temporal patterns in the model match those in the observations. The Fractional Gross Error (FGE) is a measure of the overall model error. It ranges between 0 and 2 and behaves symmetrically with respect to under- and overestimation, without over emphasizing outliers.

4. Results and discussion

4.1. Surface concentration

First, the monthly averages of PM10 for the stations listed in table 2 and the period 2013-2015 are represented in figure 3. The annual variation is fully determined by the seasonal features of the Canarian climate. The low-level intrusions of Saharan dust are more frequent in winter, especially on the easternmost islands, closer to the African continent. At the beginning of the winter season, the belt of the trade winds has moved to its southernmost position, giving way to dust-laden Saharan air masses to reach the islands.

Dust outbreaks in summer are also not uncommon. However, in this season, the circulation of the trade winds is almost permanent in the latitudes of the Canary Islands, so that the easterly winds, filled with dust, reach the archipelago only in elevated layers, while beneath them, a mass of clear, moist oceanic air, with northeasterly winds still persists. It is not by chance that the highest dust concentrations in summer are measured in Granadilla, a station located at an altitude of 580 m above sea level.

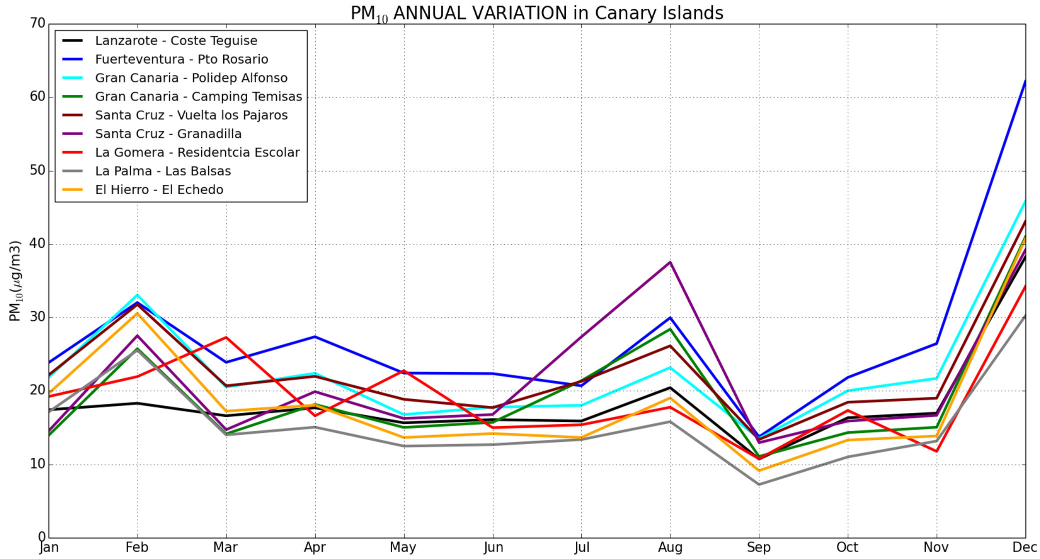

Figure 3: Monthly averages of PM10 at the selected stations

Figures 4 and 5 show monthly averages for two stations (Costa Teguise and Granadilla). The color lines show the values obtained from the forecasts of the different models with lead times between 3 and 24 hours. In particular, the blue line corresponds to the multi-model median. The solid black line shows the mean values of unfiltered PM10 (NoFilter), the dashed black line shows the monthly average of dust surface concentration estimated with the Perc40 method and the gray line shows the average estimates based on the PMcoarse method.

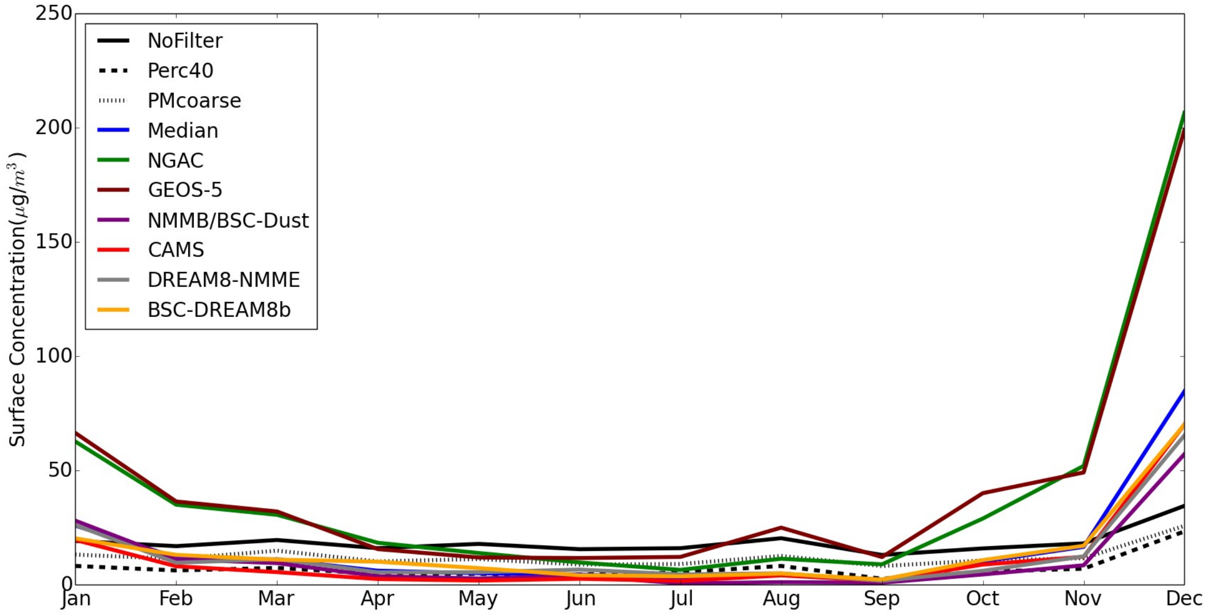

Figure 4: Monthly averages of dust surface concentration forecast by the models and estimated from PM measurements at Costa Teguise. The color lines show model-derived values. In particular, the blue line corresponds to the multi-model median. The solid black line shows the mean values of unfiltered PM10 (NoFilter), the dashed black line shows the average monthly estimates obtained with the Perc40 method and the gray line shows estimates based on the PMcoarse method.

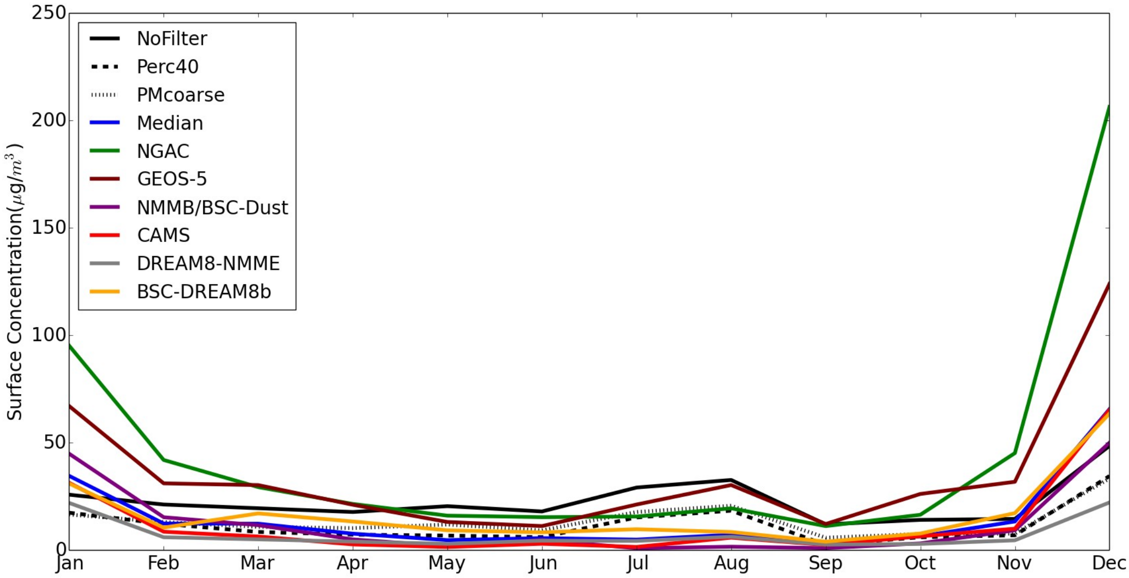

Figure 5: Monthly averages of dust surface concentration forecast by the models and estimated from PM measurements at Granadilla.

It should be noted that the average DSC estimated from PM measurements using the three methods follows a very similar annual evolution in Costa Teguise (figure 4) and Granadilla (figure 5), suggesting a constant level throughout the year of airborne particles other than mineral dust. In addition, except for Granadilla in December, estimates based on PMcoarse are higher than estimates with Perc40.

At a first glance, the models show a correct annual evolution. However, a clear overestimation of NGAC and GEOS-5 can be noted during the winter months. Also, most models do not capture the increase of summer concentration in Granadilla (figure 5). This last trait could be expected, since the increase is closely associated to the orography, whose resolution in the models is limited.

Table 4 shows the scores of the multi-model median at both sites using the methods described before. Scores have been computed from the three-hourly pairs measurement-forecast using predictions with lead times from 3 to 24 hours.

	COSTA TEGUISE			GRANADILLA		
	NoFilter	**PMcoarse**	**Perc40**	**NoFilter**	**PMcoarse**	**Perc40**
BE	-2.48	4.39	7.34	-7.83	1.22	1.63
MSRE	44.35	46.03	45.41	39.54	38.13	38.51
r	0.59	0.57	0.59	0.65	0.64	0.66
FGE	1.47	1.49	1.44	1.45	1.30	1.43

Table 4: Evaluation scores of the DSC predicted by the multi-model median at Costa Teguise and Granadilla

The results based on the three methods do not differ much (both MSRE and r yield similar values). Neither of the two correction methods to PM10 measurements seems to introduce substantial changes to the evaluation scores. Based on this, the NoFilter method – the direct use of PM10 measurements seems the better and simpler alternative

It can be clearly seen that the multi-model median, together with GEOS-5 in the case of Granadilla, presents better correlation with measurements than any other individual model for both stations and any comparison method as it is shown in the Taylor diagrams (Taylor, 2001) synthesizing the evolution of the different models for Costa Teguise (figure 6) and Granadilla (figure 7). Also, the particular behavior (strong overestimation in winter) of the NGAC and GEOS-5 models becomes evident.

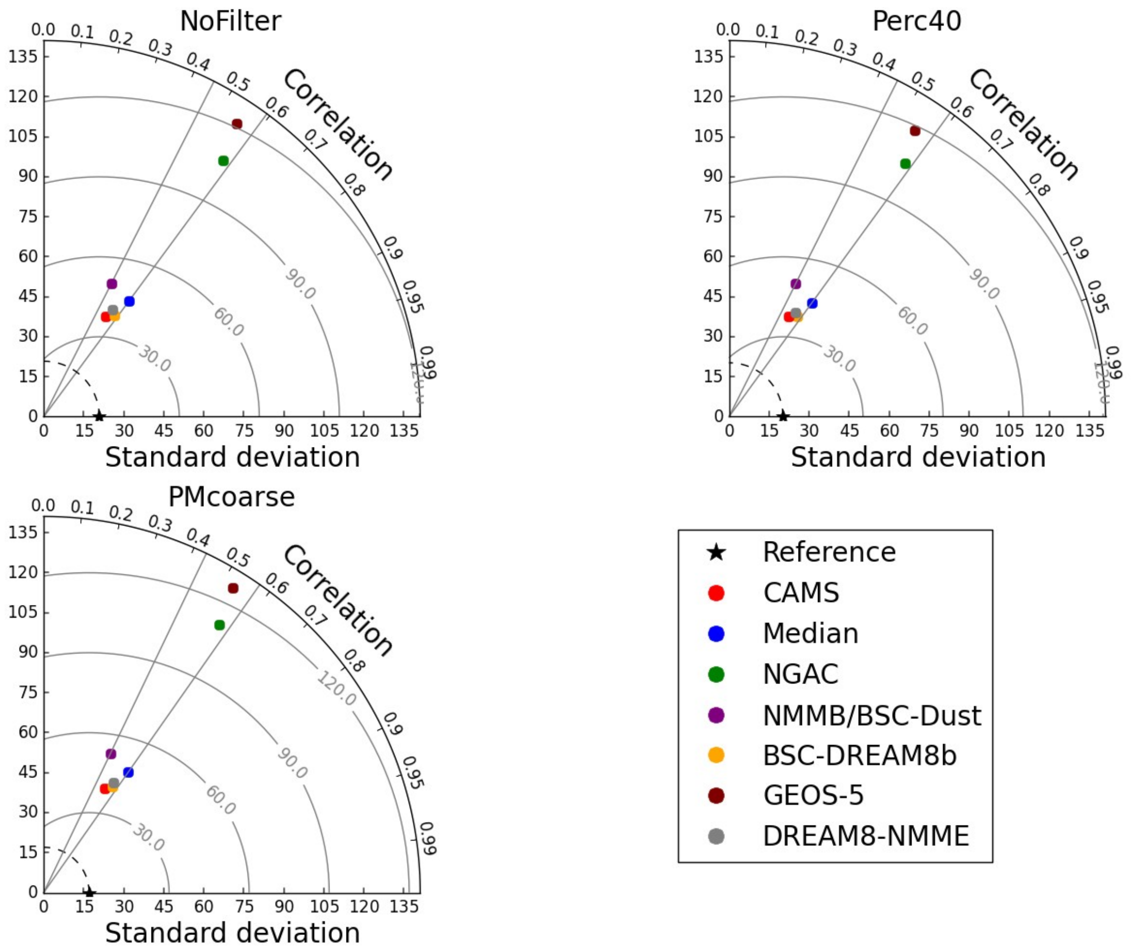

Figure 6: Taylor diagrams synthesizing the evaluation scores of the different models and comparing strategies at Costa Teguise

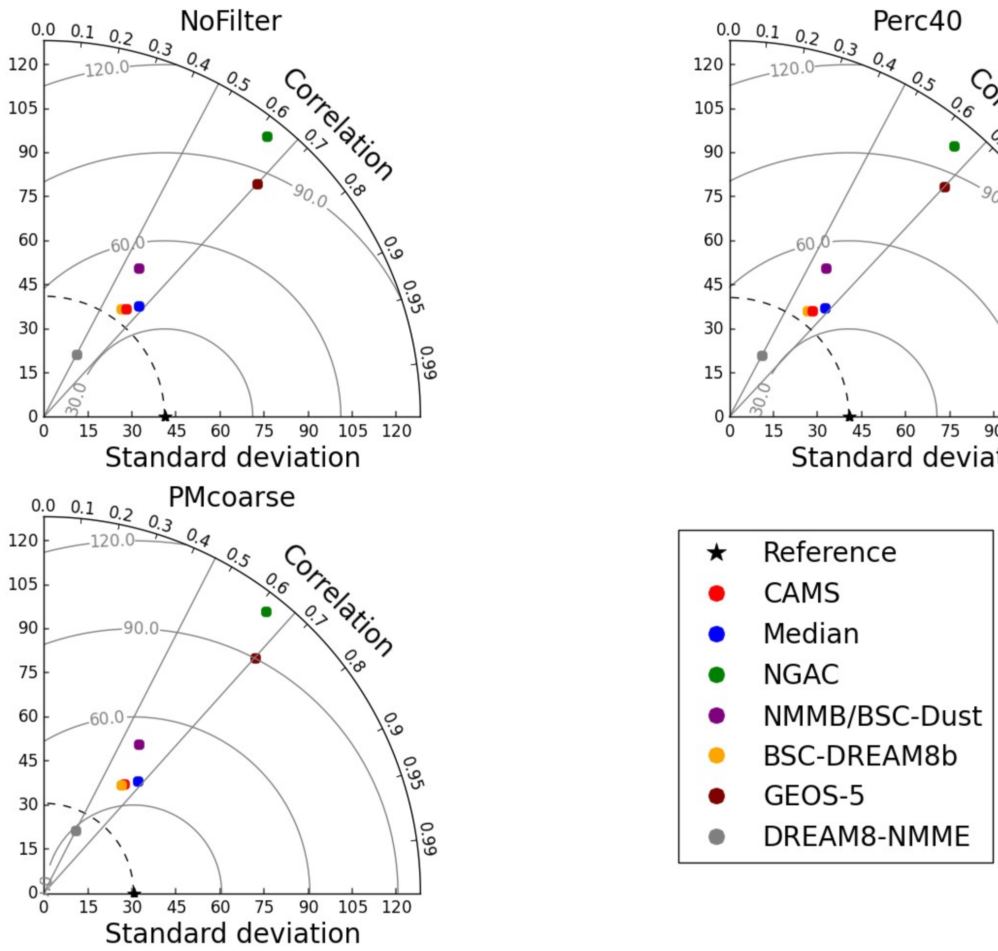

Figure 7: Taylor diagram synthesizing the evaluation scores of the different models and comparing strategies at Granadilla

Again it can be observed that there are no large differences between the three methods (the three Taylor diagrams look quite similar).

4.2. Dust optical depth

Figure 8 shows the monthly averages of AOD for the AERONET station of Santa Cruz de Tenerife and the period 2013-2015 (black thick line). The figure also shows the monthly averages of DOD based on the three methods described in Section 3.6 and on the daily simulations of the different models. Both measurements and simulations clearly reproduce an annual cycle with peak values in summer and winter.

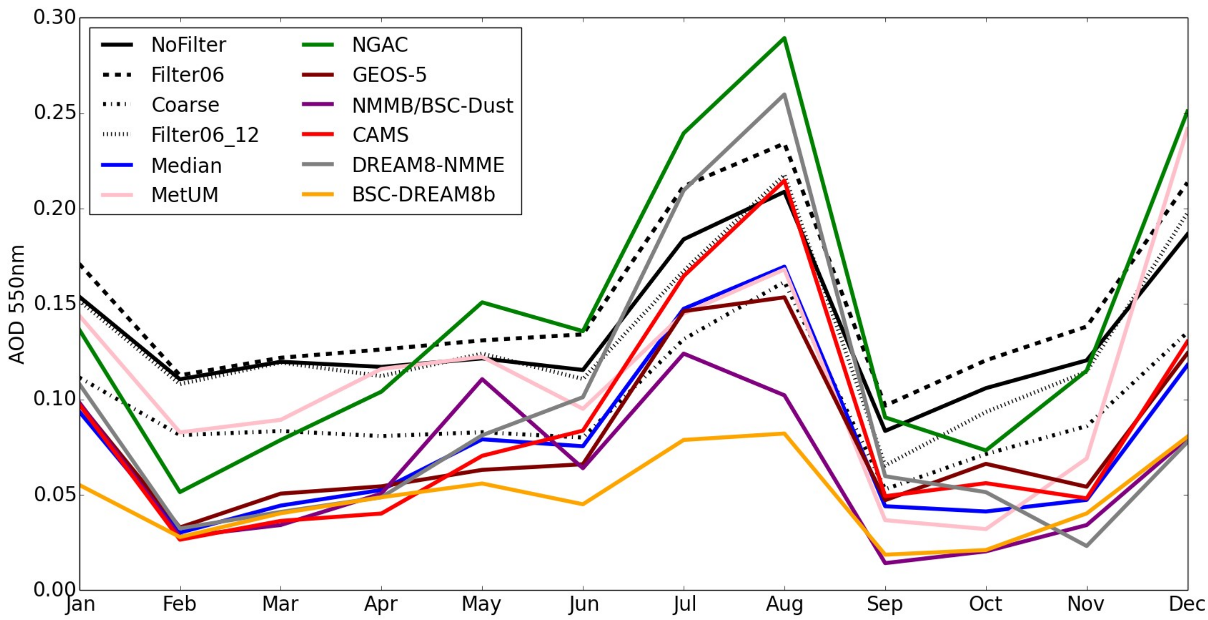

Figure 8: Monthly averages of dust optical depth estimated with different methods from the AERONET station of Santa Cruz de Tenerife and simulated by the different models

Table 5 shows the scores of the multi-model median computed using the methods described in Section 3.6.

	NoFilter	**Filter06**	**Filter06_12**	**Coarse**
BE	-0.05	-0.05	-0.04	-0.01
MSRE	0.11	0.13	0.12	0.09
r	0.84	0.83	0.84	0.85
FGE	0.96	0.83	0.97	0.80

Table 5: Evaluation scores of the DOD predicted by the multi-model median at Santa Cruz de Tenerife

As with DSC, the results based on the four methods do not differ much. However, the use of the Coarse method, that is the coarse fraction of AOD, in the evaluation can be fully justified, since the correlation coefficient is slightly higher than that obtained through the other methods and the

BE is very close to zero.

Finally, figure 9 shows the Taylor diagrams synthesizing the evaluation of the different models for Santa Cruz de Tenerife.

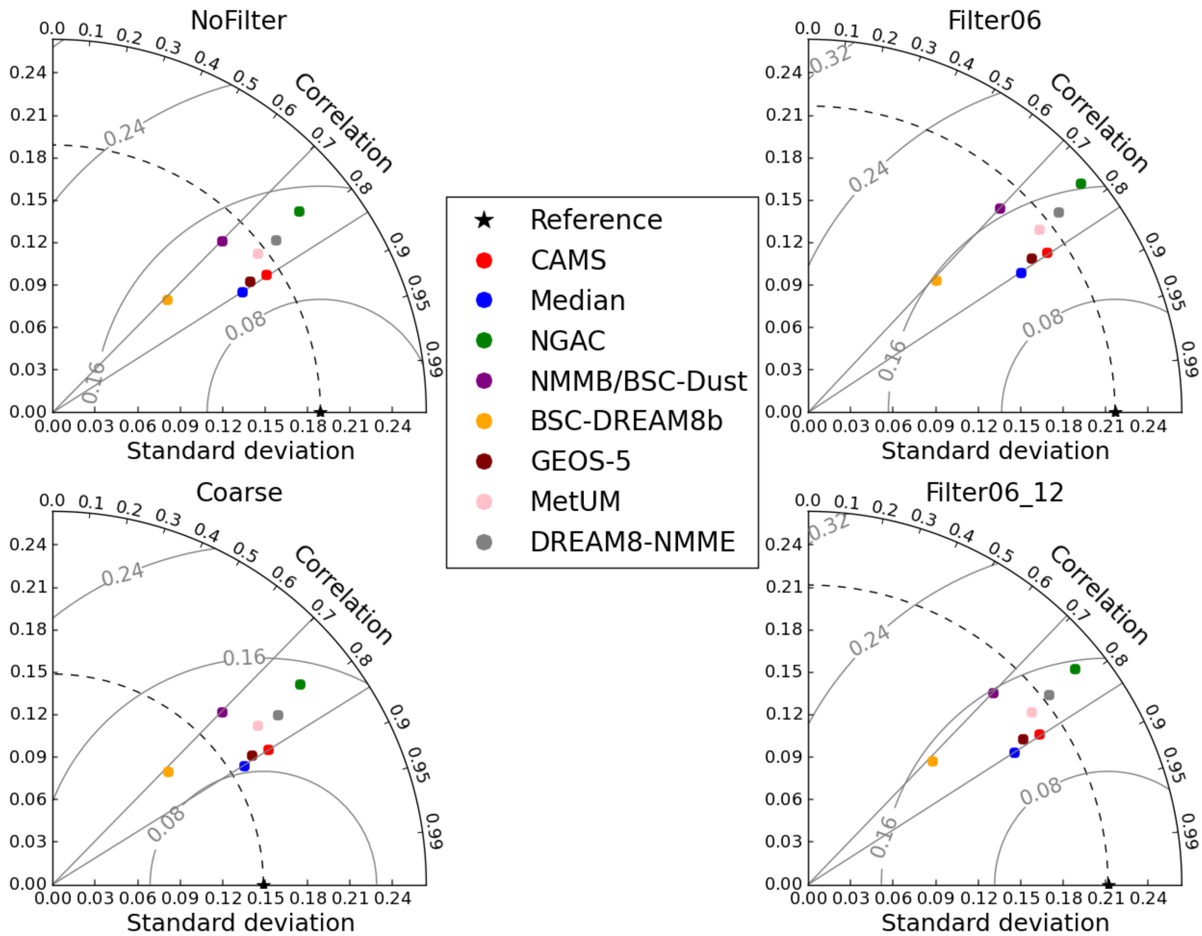

Figure 9: Taylor diagram synthesizing the evaluation scores of the different models and comparing strategies at Santa Cruz de Tenerife

In the four cases, the median, together with CAMS, presents the best correlation coefficient with measurements (0.83 – 0.85). Moreover, the median yields lower standard deviation than CAMS.

5. Conclusions

In general, models reproduce reasonably well the annual variation pattern, both of DSC and DOD. PM10 measurements from air quality monitoring stations provide useful information for model evaluation. However, correlation coefficients are much higher for DOD than for DSC. It probably means that models reproduce better the dust contents in the entire atmospheric column than the dust concentration at specific levels.

Estimates of the contribution of mineral dust to the PM10 measurements do not provide better results than the actual measurements in the evaluation of DSC predicted by the models. Contrarily, the evaluation of DOD based on the coarse fraction of AOD provided by O'Neil's spectral de-convolution algorithm (Coarse method) looks better than that based on the total AOD.

Finally, the multi-model median performs better than any individual model for the short-term forecast of airborne dust, both for DSC and DOD.

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