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Pollution and dust aerosols modulating tropical cyclones intensities

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ABSTRACT

Tropical cyclones (TC) are propelled mostly by realization of latent heat that is stored in vapor coming off warm sea surfaces. The heating occurs when the vapor condenses into cloud drops. Re-evaporation of the cloud water takes back the released heat, whereas precipitation of the water as rain fixates the heat in the air. Therefore, it is expected that TC intensities would be sensitive to precipitation forming processes that affect the amount and distribution of latent heat release. This has been simulated by numerical models, which showed that cloud condensation nuclei (CCN) aerosols weaken the storms apparently by slowing the conversion of cloud drops into precipitation. If so, we should expect that storm predictions that do not take this aerosol effect into account would over-predict TC intensities. Here we show that increased aerosols quantities in a TC periphery can explain about 8% of the forecast errors of the TC. Indeed, actual intensities of polluted TCs were found to be on average lower than their predicted values, providing supporting observational evidence to the hypothesis. It was also found that TC intensity might be more susceptible to the impacts of aerosols during their developing stages and less in the TC mature and dissipating stages.
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1. Introduction

1.1. STORMFURY and TC modification

The idea of modifying Tropical Cyclones (TCs) by aerosols through their impacts on precipitation forming processes originated with project STORMFURY (Willoughby et al., 1985). It was postulated that glaciogenic (ice forming) seeding of convective clouds just outside the eyewall would freeze their supercooled water, so that the released additional latent heat of freezing would invigorate the seeded clouds and disrupt the convergence of air into the eyewall and so weaken the maximum TC wind speed. STORMFURY was inconclusive, to a large extent because most TCs apparently do not have sufficient supercooled water. Supercooled water is scarce in convective clouds that form in marine air mass. The pristine maritime air that typically converges to TCs has small concentrations (few hundreds cm^{-3}) of cloud drop condensation nuclei (CCN), which form respectively low concentrations of large cloud drops that are fast to coalesce into raindrops. Therefore, much of the cloud water precipitates from the rising air before reaching the freezing level, thus leaving little potential for supercooled water. Rosenfeld et al. (2007) suggested that the basic idea of STORMFURY – invigoration of the periphery on expense of the center – might still work by adding CCN aerosols to the air ingested by a TC. The early rainout can be delayed by high concentrations of CCN aerosols, which form a larger number of smaller cloud drops that are slower to coalesce into raindrops (Gunn and Phillips, 1957).

The phenomenon of invigoration due to aerosols in polluted tropical convective clouds was reviewed by Rosenfeld et al. (2008). Observations of pollution invigorating convection over land in moist tropical convection were provided by Bell et al. (2008, 2009a, 2009b), but when moving to the cooler summer mid-latitudes the ice nuclei role of the pollution aerosols might be more dominant (Dessens et al., 2001). Most relevant to the present study over ocean are the observations (Koren et al., 2010) of deep tropical clouds growing taller in areas containing greater aerosol quantities as measured by the aerosol optical

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thickness (AOT) observed directly by satellites and as calculated by the Goddard Chemistry Aerosol Radiation and Transport (GOCART) hindcast model (Chin et al., 2000).

1.2. Model simulations of aerosols weakening TCs

During summer and early fall, intense heating over the Sahara desert forms a deep mixed atmospheric layer containing hot, dry air and mineral dust, which is often referred to as the Saharan Air Layer (SAL). TC weakening was observed to occur in the presence of the SAL (Dunion and Velden, 2004), but the effect was mostly ascribed to the dry air and strong middle level (~2–4.5 km) winds (i.e. enhanced vertical shear) associated with this air mass. The relationship between dust and TC intensity was not well understood at that time (Dunion and Velden, 2004). In 2008, aircraft observations of desert dust associated the presence of larger aerosol quantities with an exceptionally vigor outer band of a TC (Jenkins et al., 2008).

These observations prompted numerical simulations testing the impact of CCN activity of desert dust on TC intensities (Cotton et al., 2007; Zhang et al., 2007). This was simulated by adding 2000 CCN cm^{-3} in the area where the storms formed compared to simulations with 100 CCN cm^{-3} (considered to be "clean of pollution"). In the simulation with the 2000 CCN cm^{-3} the CCN aerosols weakened substantially the storm, with peak winds lowered by 25 ms^{-1} and central pressure higher by 25 hPa. Independently, in 2007 Rosenfeld et al. (2007) obtained similar results by simulating the invigoration achieved due to turning off the warm rain forming processes at the periphery of a TC. They showed that the suppression of warm rain led to invigoration in the periphery coupled by enhanced evaporation and cooling at the low levels that led to weakening of the TC. However, wind induced sea spray containing salt aerosols that serve as giant CCN (GCCN) restored the warm rain and reduced the simulated TC-weakening effect. Subsequent model simulations provided additional support to this mechanism and emphasized the role of cold pools of air due to evaporative cooling that weaken the storms (Carrió and Cotton, 2011; Khain et al., 2008, 2010; Khain and Lynn, 2011; Zhang et al., 2009).

2. Methodology

2.1. The storm prediction errors

In this study, we separate the aerosol from other effects by using TC prediction models that take into account all meteorological and sea surface temperature properties, but not the aerosols. If greater aerosol amounts actually act to decrease storm intensity, the forecast model would tend to over predict the observed intensities of the more "polluted" storms. We use this logic to test the hypothesis of aerosols weakening TCs. The hypothesis that aerosols can explain forecast errors of forecast models has been tested in the past by Carmona et al. (2008). Carmona et al. hypothesized that the aerosol AOT can be used as an explanatory variable in a multiple linear regression model to the forecast errors of the United Kingdom Meteorological Office (UKMO) model since this model does not take into consideration the aerosol effect on the temperature. The finding of Carmona et al. showed that increased aerosol quantity was found to be correlated with an over estimation of the temperature indicating a cooling effect due to the aerosols. Therefore, the UKMO over estimated the temperature. Including the aerosols effect to the UKMO model, could improve the accuracy of the forecasted temperature.

In this study we test whether variability in aerosols can explain TC prediction errors of models that do not take into account the impacts of aerosols. The accuracy of three very different operational TC prediction models was examined. The first model is The Geophysical Fluid Dynamics Laboratory model (GFDL) (Bender et al., 2007). This model was chosen since the GFDL model has up to now been the only purely dynamical model that can provide both skillful intensity and track forecasts. GFDL is based on numerical weather prediction simulations solving the equations of motion and thermodynamics of the atmosphere and coupled with the ocean. The second model is the Statistical Hurricane Intensity Prediction Scheme (SHIPS) (DeMaria et al., 2005). These two models were chosen to be examined in this study because they are the primary guidance models that the National Hurricane Center (NHC) uses for its operational intensity forecasts.

The SHIPS model is multiple regression scheme which incorporates climatology, atmospheric environmental parameters (vertical shear, etc.) and sea surface temperature (SST) as its predictors. The third model is Decay-SHIPS which is a forecast model just like SHIPS, however, incorporates the decaying effect of land on TC intensity.

The historical record of model predictions and actual TC maximum sustained wind speeds (Vmax) were obtained from the Automated Tropical Cyclone Forecast (ATCF) database (Miller et al., 1990) available online from the National Oceanic and Atmospheric Administration (NOAA). The wind speeds are given in knots, where 1 knot is 1.852 km h^{-1}. The data is available at time steps of 6 h for lead times of 0 to 120 h. This study examines the prediction errors of Vmax at the forecast lead times of 12, 24, 36 and 48 h in order to test our hypothesis on the most accurate forecasts. A forecast with a lead time of zero is practically the observations.

The Vmax prediction error is defined as

$$dV\ \max = \mathrm{Vmax}_{\mathrm{obs}} - \mathrm{Vmax}_{\mathrm{predict}} \quad (1)$$

where $\mathrm{Vmax}_{\mathrm{obs}}$ is the observed Vmax and $\mathrm{Vmax}_{\mathrm{predict}}$ is the predicted Vmax. For each forecast model dVmax values were calculated for each of the four lead times. This study used all the available ATCF data for 2001–2007 for all Atlantic TCs that reached hurricane force winds at some time during their lifecycle and were tracked for at least 48 h. The minimum intensity for tracking a TC, in our data base was 25 kt. The analysis could not be extended beyond 2007 because the aerosol data used here were not available beyond that year.

Anthropogenic aerosols, as well as dust originate from the continents. For this reason, aerosol quantities usually increase in the TCs peripheries when the storms reach landfall. TC intensity is known to decay during landfall. Therefore, in order to associate the decay of TC to aerosols and not due to landfall, all landfall TC data were excluded from this study. Thus, in the data sets of this study, aerosol quantities are not associated with landfall. If a statistical relationship is found between increased aerosol quantities in the TC periphery to a decrease in TC intensity, it may be attributed to the microphysical effect that

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aerosols might have on the TC peripheral clouds, and not due to their association with land.

The forecasts of the SHIPS and D-SHIPS models differ only when a TC is at least partially over land. This difference was used in order to identify the data points over land in the data sets and exclude them from the statistical analysis. From here on, the study will discuss the GFDL forecast errors and the SHIPS forecast errors, because once land is excluded from the D-SHIPS and SHIPS, they become identical.

In order to compare the forecast accuracy of GFDL and SHIPS, the standard deviation (SD) of dVmax was compared at each lead time. Fig. 1 shows the SD of dVmax as a function of the forecast lead times of 12, 24, 36 and 48 h, for the GFDL and SHIPS forecast models. As the lead time increases, the SD of dVmax increases. This signifies that the forecasts become less accurate and contain more noise with increased lead times.

Fig. 1 shows that SHIPS forecast error has a much lower standard deviation in all lead times which coincides with the fact that SHIPS is a much more accurate intensity forecast model. These findings coincide with the NHC 2005 annual verification report comparing model performance to the official NHC forecast, which found that GFDL provided the best shorter-range track forecasts while SHIPS was the best performer in the intensity forecast models (Franklin, 2006).

2.2. The Goddard Chemistry Aerosol Radiation and Transport model

The aerosol data, in the form of aerosol optical thickness (AOT) was obtained from GOCART, which calculates the AOT for black carbon (BC), organic carbon (OC), dust (DU), sea salt (SS) and sulfate (SU). The model uses the assimilated meteorological fields generated from the Goddard Earth Observing System Data Assimilation System (GEOS DAS) (Schubert et al., 1993).

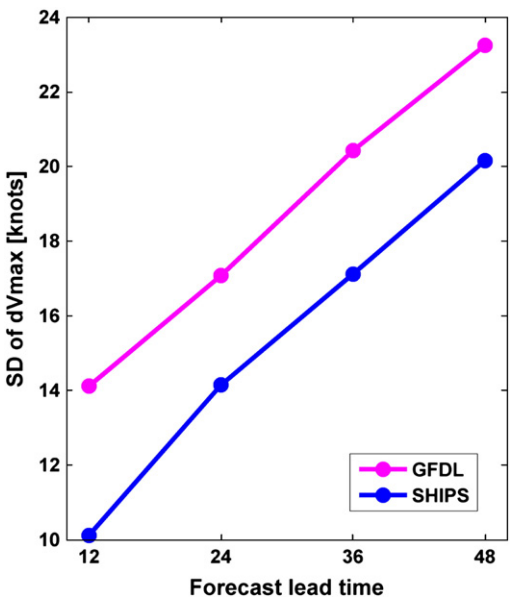

Fig. 1. The standard deviation of the TC maximum sustained wind speed prediction errors (dVmax) as a function of the prediction lead time for the GFDL and SHIPS models.

The reliability of the results in this study depends on the accuracy of the GOCART AOTs. Therefore the performance of GOCART is reviewed here briefly. Since 2000, the capability of GOCART to hindcast aerosol quantities has repeatedly put to test in different studies by comparing its AOT values to ground measurements, satellite imagery and aircraft observations. Comparisons between the simulated and observed sulfate concentrations agreed within 30% and captured the local and regional features in both marine boundary layer and free troposphere (Chin et al., 2000). Comparisons of GOCART simulations to aircraft measurements of dust and sulfates showed that the GOCART model agreed with the observation of individual aircraft flight at various heights (Chin et al., 2003). In 2004 daily AOT from GOCART was compared with the Aerosol Robotic Network (AERONET) data over the northern hemisphere (Chin et al., 2004) both producing comparable values and similar probability distributions. Daily comparisons with AERONET at several sites are given also in Chin et al. (2009) and show good correspondence. In 2007 GOCART simulated BC, OC and fine mode dust were compared to daily ground measurements over the U.S at 135 sites in the IMPROVE network during 2001 (Chin et al., 2007). These comparisons showed that the model captures the spatial and temporal variations of the observed aerosols with high correlation and low bias. A high correlation of 0.756 between GOCART and IMPROVE was found on a monthly average while the daily correlations varied mostly between 0.4 and 0.7. In 2010 comparisons with the Cloud–Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) observations showed generally consistent characterization of both magnitude and altitude of trans-Atlantic transport of Saharan dust, with quantitative agreement within 30% for individual observations (Yu et al., 2010).

Koren et al. (2010) used daily data from both GOCART simulations and MODIS observations for testing the hypothesis of aerosol induced invigoration of deep maritime convective clouds. They found that regions with larger AOT are associated with clouds having significantly greater cloud top heights. Cloud invigoration and increased AOT relation was obtained with similar clarity from both GOCART and MODIS AOTs for convective clouds over the Atlantic and pacific Oceans, independently. This demonstrates the applicability of GOCART calculated AOT to the central theme of our study, as well as providing support to the basis of our hypothesis.

2.3. The data set

Two data sets were constructed; one for the GFDL forecast errors and one for the SHIPS forecast errors. The data sets contain the TC location (latitude and longitude of the center of the storm), measured Vmax, the calculated dVmax for each prediction lead time, the calculated averaged AOT at the TC periphery for each aerosol type and the averaged precipitable water (PW). The PW data was incorporated in this study in order to examine of aerosols affect TC intensity due to their microphysical activity or because they are associated with dry air. PW data was obtained from National Centers for Environment Protection/National Center for Atmospheric Research (NCEP/NCAR) reanalysis data. The TC periphery was defined to

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be at the radius of 300 km from the center of the TC, which encompasses the maximal radius of most TCs. The averaged AOT represents the aerosols that are ingested into the periphery of the TC. Unlike satellite data, the GOCART AOT is not affected from the clouds and is solely representing aerosol concentration. The results were found to be insensitive to the selected radius, so that only the analysis for radius of 300 km is reported.

3. Results

3.1. Relations between the various aerosol species, precipitable water and dVmax

The main reason for examining the correlations between the AOT of different aerosol types is to check for the possibility of multicollinearity. Multicollinearity is a statistical phenomenon in which two or more explanatory variables in a multiple regression model are highly correlated. In this situation the coefficient estimates may have large standard errors and thus the parameter estimates may change erratically in response to small changes in the model or the data.

When examining the correlations between the different aerosol AOT at the TC periphery (Fig. 2), three salient features were found. The first, the three anthropogenic aerosols: BC, OC and SU were found to be highly correlated with each other. The second, higher DU quantities were found to be correlated with moderate values of the three anthropogenic aerosols. The third, higher amounts of anthropogenic aerosols were not found to be correlated with dust. These three features can be explained by GOCART calculation of their quantities and transportation. In the Atlantic basin, the main source of dust is the African desert. However, the anthropogenic aerosols have two sources: North and South America and Africa. North and South America produce substantial amounts of the three anthropogenic aerosols, while moderate quantities are produces by the African continent. Therefore, wind currents from Africa advect both dust and the three aerosols, whereas air currents from the American continents advect only the three anthropogenic aerosols with little or no dust. For this reason, higher dust quantities were found to be associated with moderate quantities of the three aerosols, while higher quantities of the three aerosols were not found to be statistically correlated with dust. These findings indicate that in the data set used in this study, all four of these aerosols are not independent of each and may oppose a multicollinearty problem when using all four as independent explanatory variables in a regression model where the dependent variable is the intensity forecast errors.

TC intensity was found to be positively correlated with the averaged value of PW at the TC periphery (Fig. 3a), indicating the strong effect of vapor availability on TC intensity. In contrast, PW is poorly correlated with dVmax (Fig. 3b and c). The minor or lack of correlation of the forecast errors with PW indicates that the models already account fully for the effects of humidity on intensity.

The next step was to examine the correlations between the different aerosols and PW. Between the four aerosols, only dust was found to be negatively correlated with PW, indicated that dust is associated with drier air (Fig. 4). However, due to the lack of correlation between PW to dVmax, any negative association between these aerosols to dVmax may be explained by their microphysical effects and not from their presence marking drier air. The goal of this study is to try and single out

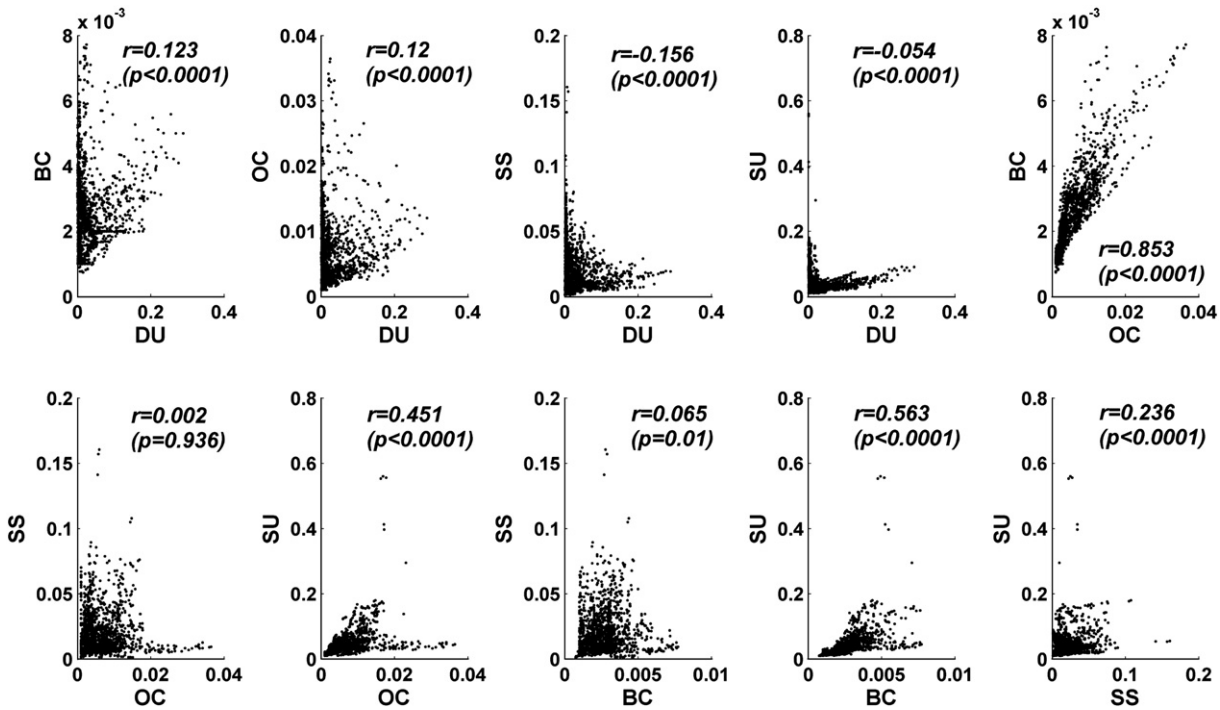

Fig. 2. Scatter plots between the AOT of black carbon (BC), dust (DU), organic carbon (OC), sea salt (SS) and sulfate (SU). The figure presents the correlations with their statistical significance in brackets calculated from a data set of 1553 points.

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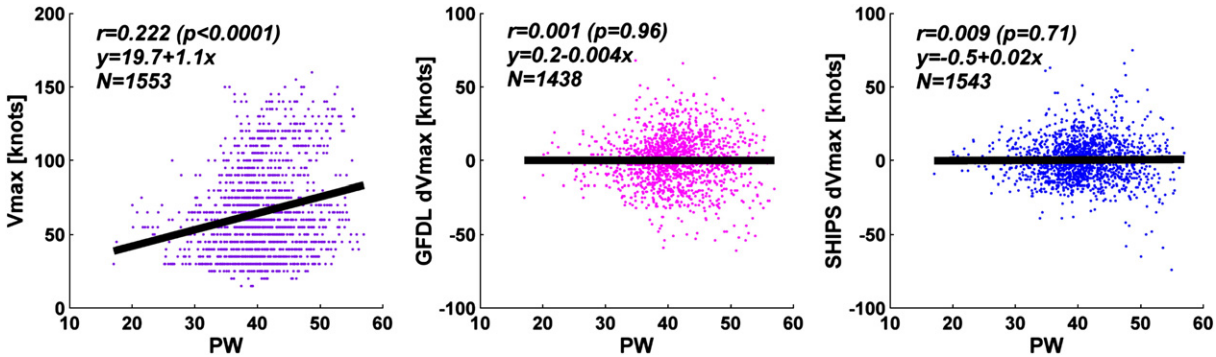

Fig. 3. From left to right, scatter plots between the precipitable water (PW) [kg m^{-2}] to TC intensity (Vmax [knots]), GFDL and SHIPS intensity forecast errors, dVmax [knots], respectively. The figure includes the size of each data set, the Pearson correlation, its statistical significance in brackets and the simple linear regression relationships between PW to Vmax (left) and dVmax (middle and right figure).

the signal from only the aerosols and weed out other factors which might contribute to the patterns between aerosols and the forecast errors.

3.2. A GLM Model

After statistically analyzing the relationships between the different aerosols the next step was to try a fit of a regression model where the aerosols serve as explanatory variables to dVmax. The GOCART values of aerosol AOT of DU, BC, OC and SU, averaged at the TC periphery, were chosen to serve as explanatory variables in the regression model, while SS could not serve as an independent variable to dVmax since its value over ocean is dependent on wind speeds (Chin et al., 2002). In the regression model, the dependent variable dVmax within each TC is given as a series of measurements over time that have a serial autocorrelation, while observations in different TCs are independent. This covariance structure may be accounted for by using a general multiple linear regression model (GLM) (SAS PROC MIXED, (SAS Institute Inc., 2004)). To comply with the statistical model assumption of homogeneity of the error variance, the explanatory variables were transformed into their natural logarithm. Another consideration which needed to be made was the removal of extreme values of residuals in order for the residuals to be normally distributed. The removal of these data points excluded dVmax values which were considered to be outliers. The cutting off point was the absolute residual value that exceeded three standard deviations. This excluded 0.83% and 1.36% from the GFDL and the SHIPS data points, respectively.

When all four of the aerosols: BC, DU, OC and SU were used as four different explanatory variables in the GLM for the dependent dVmax, none of these explanatory variable coefficients estimates reached statistical significance (Table 1). The failure of each aerosol type to serve as an explanatory variable to the forecast intensity error could be explained by two reasons. Either the aerosols in the TC periphery cannot explain the variance of dVmax for neither GFDL nor SHIPS, or, each aerosol as an independent explanatory variable cannot explain variance in dVmax. In order to explore the latter, two new variables were created: Pollution, which is the sum of the three anthropogenic aerosols in the periphery and total aerosols AOT (TAOT), which is the sum of all four of the aerosols used in this study.

For each forecast model four GLMs were constructed for the model forecast lead time of 12, 24, 36 and 48 h. In each lead time four different combinations of explanatory variables were tested. The first run included only one explanatory variable, the TAOT, the second run attempted to differentiate the effects of anthropogenic aerosols and dust by using two explanatory variables: pollution and dust as two different explanatory variables. Runs three and four used one

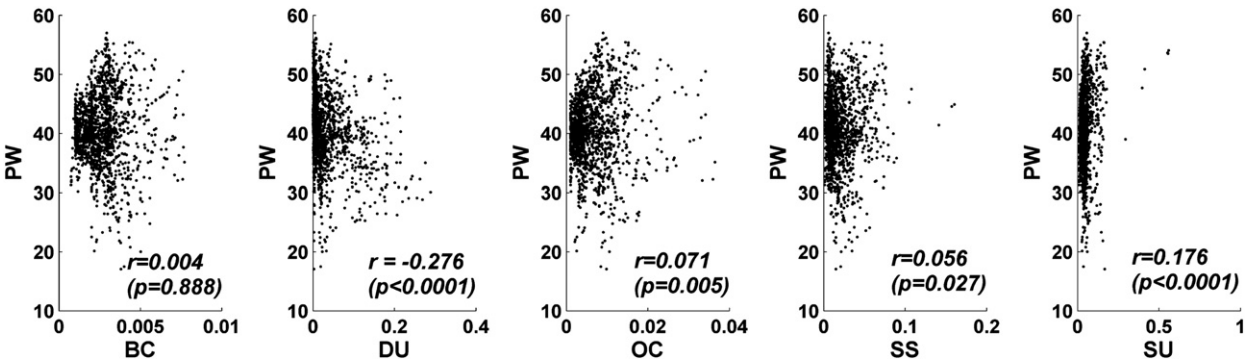

Fig. 4. Scatter plots between the AOT of black carbon (BC), dust (DU), organic carbon (OC), sea salt (SS) and sulfate (SU) to precipitable water (PW) [kg m^{-2}]. The figure presents the correlations with their statistical significance in brackets calculated from a data set of 1553 points.

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Table 1
The multiple regression coefficients and significance levels for explanation of variability in dVmax [knots] as a function of AOT of dust, organic and black carbon GOCART calculated aerosols. The dependents are the intensity forecast errors for values that are for GFDL and SHIPS predictions of 24 h lead time.

Forecast lead time: 24 h		
Forecast model	GFDL	SHIPS
N of cases	1426	1522
Black carbon	−1.6599 (0.6497)	2.1355 (0.4489)
Dust	−0.2475 (0.7178)	−0.4129 (0.4340)
Organic carbon	−1.8349 (0.3979)	−1.3647 (0.4155)
Sulfate	2.299 (0.255)	−1.0910 (0.4869)
Intercept	−13.3387 (0.3088)	−0.2385 (0.9812)

explanatory variable, pollution and dust, respectfully. The results are presented in Table 2 for the forecast errors (dVmax) of the two forecast models at the forecast lead time of 12, 24, 36 and 48 h. From Table 2, it is apparent that the most suitable explanatory variable to dVmax is the TAOT due to its highest statistical significance. The GLM for the lead time of 36 h presents the strongest signal for the aerosols since it is the only lead time for which both the total aerosols AOT (TAOT) of SHIPS and GFDL are statistically significant and similar. In the case for SHIPS it is apparent that as the lead time increases, the coefficient estimates for the TAOT variable increased in value and statistical significance.

Aside from statistical significance, the TAOT coefficient values can also be compared between the different GLMs at the different lead times according to the signal to noise ratio. Here, the noise is the error of the forecast model established by the standard deviation of dVmax (Eq. 3) and the signal is the TAOT effect on dVmax as found in Table 2. As the lead time increases, the accuracy of dVmax decreases. This is apparent in Fig. 1, which showed how the standard deviation of dVmax for both GFDL and SHIPS dVmax increased with the increased lead time. In order to calculate the signal to noise ratio, the effect of adding one standard deviation of the TAOT coefficient was calculated according to Eq. 2.

$$\text{signal} = C_{TAOT}\log(\,meanTAOT + sdTAOT) - C_{TAOT}\log(meanTAOT) \tag{2}$$

$$noise = SD\ of\ d\text{Vmax} \tag{3}$$

Where C_{TAOT} is the coefficient estimate for the TAOT variable, *meanTAOT* is the average value of the TAOT in all the data and *sdTAOT* is its standard deviation. The SNR calculation for each forecast model in each lead time is presented in Table 3.

The SNR values support the findings of Table 2 which is that the aerosols effect on the forecast errors is the most significant for the GFDL dVmax of lead time for 36 h. For SHIPS dVmax both the lead time of 36 and 48 gave similar SNR values.

In order to get a quantitative example of how increased AOT in the TC periphery affects dVmax, the coefficient estimate of the total aerosol AOT for both GFDL and SHIPS dVmax at the lead time of 36 h were plugged into Eqs. 4 and 5, which represent the GLM with and without the explanatory variable transformation to its natural logarithm. This created two different sets of equations, one for each forecast model. In Eqs. 4 and 5, the parameters A and B represent the intercept and C and D the TAOT coefficient estimate for the logarithmic and linear transformation, respectively. The coefficient estimates for the lead time of 36 h with and without the logarithmic transformation appear in Table 4.

$$d\text{Vmax}_{log} = A + C_{TAOT}log(TAOT) \tag{4}$$

$$d\text{Vmax}_{\text{linear}} = B + D_{TAOT}\cdot TAOT \tag{5}$$

Eqs. 4 and 5 were used to calculate the effect of increasing the aerosol variable with respect to its average value. Two different methods of increasing the TAOT about the mean

Table 2
The logarithmic multiple regression coefficients and their significance level (in brackets) for explanation of variability in dVmax [knots]. The values are for GFDL and SHIPS predictions of 12, 24, 36 and 48 h lead time. The explanatory variables for dVmax are: total aerosol AOT (TAOT) for Run 1; dust and pollution for Run 2;. Pollution for Run 3; and Dust for Run 4. The numbers in bold are statistically significant at the 0.05 level.

Lead Time		12 h		24 h		36 h		48 h	
Forecast model		GFDL	SHIPS	GFDL	SHIPS	GFDL	SHIPS	GFDL	SHIPS
N		1531	1591	1426	1522	1311	1441	1179	1338
Run 1	TAOT	−1.4797 (0.1345)	−0.7151 (0.2050)	−1.3206 (0.3128)	−1.8107 (0.0746)	**−3.2829 (0.0492)**	**−2.6350 (0.0420)**	−1.1704 (0.5463)	**−3.2552 (0.0341)**
	Intercept	−2.8636 (0.2859)	−1.0986 (0.4716)	−3.5072 (0.3269)	−5.2052 (0.0604)	−9.6304 (0.0361)	−8.6681 (0.0152)	−4.6334 (0.3863)	−12.3489 (0.0040)
Run 2	Pollution	0.5550 (0.5939)	−0.4397 (0.4705)	−0.3967 (0.7741)	−1.1187 (0.3111)	−2.8782 (0.0984)	−2.3923 (0.0862)	−1.3277 (0.5048)	−2.7964 (0.0897)
	Dust	**−1.4633 (0.0028)**	−0.07932 (0.7714)	−0.5815 (0.3842)	−0.4523 (0.3790)	0.1381 (0.8742)	−0.1424 (0.8376)	0.8755 (0.4042)	−0.1411 (0.8693)
	Intercept	−3.5738 (0.3742)	−0.9197 (0.6917)	−3.7794 (0.4829)	−5.8435 (0.1636)	−9.1657 (0.1798)	−9.7236 (0.0673)	−1.7547 (0.8252)	−13.0150 (0.0384)
Run 3	Pollution	0.8208 (0.4350)	−0.4241 (0.4842)	−0.3132 (0.8200)	−1.0781 (0.3277)	−2.8877 (0.0963)	−2.3924 (0.0857)	−1.4101 (0.4768)	−2.8121 (0.0872)
	Intercept	3.5285 (0.2862)	−0.5336 (0.7797)	−1.0000 (0.8175)	−3.7823 (0.2765)	−9.7982 (0.0730)	−9.1082 (0.0386)	−5.8422 (0.3488)	−12.4503 (0.0176)
Run 4	Dust	**−1.4846 (0.0023)**	−0.06322 (0.8159)	−0.5253 (0.4302)	−0.4181 (0.4130)	0.2164 (0.8034)	−0.1482 (0.8314)	0.9083 (0.3854)	−0.2125 (0.8053)
	Intercept	−5.3694 (0.0147)	0.5045 (0.6793)	−2.3767 (0.4370)	−2.2794 (0.3263)	−0.04040 (0.9920)	−2.4592 (0.4438)	2.4270 (0.6172)	−4.8254 (0.2284)

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Table 3
Signal to noise (SNR) calculation for both GFDL (left) and SHIPS (right) intensity forecast errors for the lead times of 12, 24, 36 and 48 h. The absolute value of the signal is represented.

Lead time	GFDL			SHIPS		
	Noise	Signal (abs)	SNR	Noise	Signal (abs)	SNR
12 h	14.12	0.781	0.055	10.12	0.377	0.037
24 h	17.08	1.264	0.041	14.15	0.931	0.067
36 h	20.43	1.709	0.085	17.12	1.391	0.081
48 h	23.25	0.618	0.026	20.16	1.718	0.085

Table 4
The same as Table 2, but for lead time of 36 h, with and without logarithmic transformation.

Lead time: 36 h					
Forecast model		GFDL		SHIPS	
N of cases		1311		1441	
Transformation		Logarithmic	Linear	Logarithmic	Linear
Run 1	TAOT	**−3.2829**	−30.3452	**−2.6350**	**−25.4859**
		(0.0492)	(0.0669)	**(0.0420)**	**(0.0433)**
	Intercept	**−9.6304**	1.6836	**−8.6681**	0.5026
		(0.0361)	(0.3949)	**(0.0152)**	(0.7566)
Run 2	Pollution	−2.8782	−24.6646	−2.3923	−27.4035
		(0.0984)	(0.2627)	(0.0862)	(0.1448)
	Dust	0.1381	−38.1612	−0.1424	−23.7099
		(0.8742)	(0.1328)	(0.8376)	(0.1882)
	Intercept	−9.1657	1.5734	−9.7236	0.5539
		(0.1798)	(0.4333)	(0.0673)	(0.7401)
Run 3	Pollution	−2.8877	−24.7709	−2.3924	−28.8988
		(0.0963)	(0.2580)	(0.0857)	(0.1232)
	Intercept	−9.7982	0.4748	−9.1082	−0.1295
		(0.0730)	(0.7978)	(0.0386)	(0.9348)
Run 4	Dust	0.2164	−38.3283	−0.1482	−25.3816
		(0.8034)	(0.1311)	(0.8314)	(0.1596)
	Intercept	−0.04040	0.1215	−2.4592	−0.9941
		(0.9920)	(0.9368)	(0.4438)	(0.4460)

were conducted. The first method was to calculate the effect of increasing AOT 0.01 from the average value of the TAOT. The second method was to increase of the TAOT by its standard deviation (specified in Fig. 5) for obtaining a more realistic estimate of the effect of the aerosol variability on the intensity forecast errors. The validity of these calculations is limited to addition of AOT within the limited range of the observed variability of the TAOT, as given in Fig. 5. The results are given in Table 5 for both equations of the two forecast models. Fig. 5 also shows the relationship between the increased total aerosol AOT to dVmax.

In Table 5, it is apparent that the effect of increasing the TAOT quantity on the values of the dVmax was similar for both the linear and logarithmic transformation, thus assuring the statistical accuracy of the GLM. According to Table 5, an increase of 0.01 in the total aerosols AOT incurs a reduction of nearly ~−0.2 to ~−0.3 knots in dVmax, as calculated with both the logarithmic and linear regression models based on all the two forecast models: GFDL and SHIPS for the 36 h lead time. In Fig. 5 it is apparent that dVmax values decrease as a function of increased total aerosol AOT. Thus, as the aerosol quantity increases in the TC periphery, the forecast models are more likely to overestimate the TC intensity. An increase of one SD of TAOT incurs a decrease of 1.39 knots according to the SHIPS GLM and 1.73 knots according to the GFDL GLM. Comparing the aerosol signal to the noise, one SD of dVmax, at the lead time of 36 h shows that this decrease can account for 8.1% of the forecast errors of SHIPS and 8.5% if the forecast errors of GFDL. For both forecast models, aerosols were found to be able to explain the same variance in the intensity forecast errors. This indicates that if aerosols were to be included in these forecast models, they would affect the TC intensity in the same manner. The fact that adding the aerosols to the forecast model in the calculation of TC intensity can improve SHIPS predictions implies that the predictors of SHIPS are not strongly correlated with the aerosols.

The robustness of the statistical analysis was tested by repeating all the analyses on the data partitioned into three periods: 2001–2002, 2003–2004, and 2005–2007. This partition has the most similar number of cases in each subset. The results for the total aerosol AOT (TAOT) (run 1 in the previous tables), which was chosen as the run to signify the aerosols

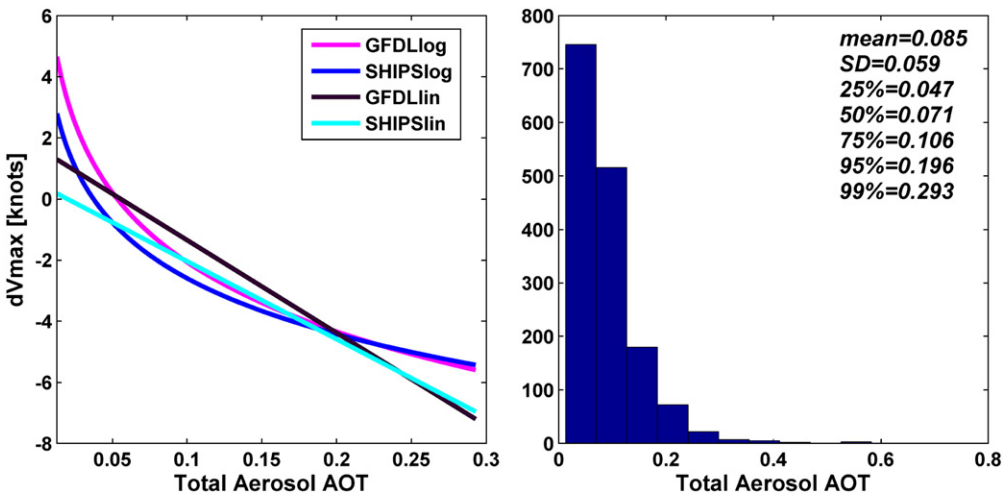

Fig. 5. Left: dVmax as a function of the total aerosols AOT (Eqs. 4 and 5) for the GLM received for the forecast models. Solid lines represent the logarthmic relationships and the broken line for the linear relationship. Right: the distribution of the total aerosols AOT, with its descriptive statsitcs.

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Table 5
Sensitivity [knots] of dVmax to increasing AOT of one of the aerosols by 0.01 from its average values and increasing AOT by their standard deviation as shown in Fig. 2. The additions were done while keeping the total aerosol AOT at its average values as shown in Fig. 2.

Forecast model	Effect of increasing AOT by 0.01 log	Effect of increasing the AOT by 0.01 linear	Effect of increasing AOT by the AOT SD log	Effect of increasing AOT by the AOT SD linear
GFDL	−0.37	−0.3	−1.73	−1.79
SHIPS	−0.3	−0.25	−1.39	−1.5

Table 6
The logarithmic multiple regression coefficients the total AOT (TAOT) and their significance levels for explanation of variability in dVmax [knots] in each period. The values are for GFDL and SHIPS predictions of 36 h lead time.

Partitioning	Explanatory variables	GFDL	SHIPS
2001–2002	N	335	365
	TAOT	−4.9199	−3.3884
		(0.1443)	(0.2144)
	Intercept	−21.1756	−14.095
		(0.0403)	(0.909)
2003–2004	N	424	479
	TAOT	−5.5441	−2.0484
		(0.0663)	(0.3295)
	Intercept	−10.7337	−4.7083
		(0.1782)	(0.3910)
2005–2007	N	553	596
	TAOT	−2.8982	−3.2992
		(0.2426)	(0.1219)
	Intercept	−7.8841	−10.3163
		(0.2308)	(0.0699)

effect on TC intensity, are replicated with rather remarkable similarity for both the SHIPS model and the GFDL model (Table 6). This statistical analysis suggests that the results found are not arbitrary since they are replicated in the annual segments with rather remarkable similarity. Although, not statistically significant, the coefficient estimates are similar to those received in Table 2 and also, are similar between GFDL and SHIPS.

3.3. Partitioning of tropical cyclones according to geographical location

Desert dust originates from the Sahara, and therefore affects mainly the eastern Atlantic while its concentration diminishes westward. Respectively, the analysis was repeated for the SHIPS model dividing the dataset into three equal sample size according to longitudinal bands, $\Phi \leq -68.4$; $-68.4 < \Phi \leq -52.9$; $\Phi > -52.9$, where Φ is the longitude in degrees. This partition was chosen in order to examine if the coefficient estimates would alter in respect to the proximity to the continents (Africa and America). The partitioning of the GFDL into regions did not yield statistically significant results; however, SHIPS did (Table 7). The partitioning of the SHIPS data to three different regions for the SHIPS data shows that the relation of Total Aerosol Optical thickness (TAOT) with dVmax is negative for all regions, but becomes statistically significant only for region 3.

Due to the high correlations between all these explanatory variables it is not clear if dust in region 3, in run 4, is significant on its own merit, or due to its correlation with the other aerosols, therefore, the attribution of the negative effect on the TC intensity cannot be made with respect to any specific type of aerosol.

In region 2, run 4 it is seen that dust as the sole explanatory variable although negative, is not statistically significant. Therefore, relating the indicated effect in regions 2 as well as in region 3 to the dust itself would be incorrect, as the dust

Table 7
The logarithmic multiple regression coefficients and their significance levels for explanation of variability in dVmax [knots] in each region. The values are for GFDL and SHIPS predictions of 36 h lead time. Run 1 is with the variable total aerosol AOT (TAOT) as the explanatory variable for dVmax. Run 2 is with the explanatory variables: dust and pollution .Run 3 is with the variable pollution as the explanatory variable. Run 4 is with the variable dust as the explanatory variable. The numbers in bold are statistically significant on a 0.05 level.

Lead time 36 h							
Region		Region 1		Region 2		Region 3	
Forecast model		GFDL	SHIPS	GFDL	SHIPS	GFDL	SHIPS
Number of data points		435	449	441	483	436	511
Run 1	TAOT	−2.0318	−0.8854	−1.5736	−0.7570	−2.9964	**−3.7301**
		(0.5569)	(0.7650)	(0.5944)	(0.7204)	(0.1707)	**(0.0407)**
	Intercept	−6.5950	−4.8126	−4.3200	−2.0165	−6.9423	−9.4076
		(0.4579)	(0.5316)	(0.6290)	(0.7524)	(0.2229)	(0.0471)
Run 2	Pollution	−2.2517	−1.4317	0.8860	4.3333	−4.4416	**−2.8216**
		(0.4831)	(0.5973)	(0.7877)	(0.0690)	(0.2051)	**(0.0194)**
	Dust	3.2428	**3.6955**	−1.3990	**−2.9320**	−0.2996	0.9094
		(0.0855)	**(0.0205)**	(0.4566)	**(0.0287)**	(0.8402)	(0.7292)
	Intercept	9.4522	12.8253	−2.6190	2.6567	−14.7378	−6.7291
		(0.5180)	(0.3010)	(0.8265)	(0.7558)	(0.1459)	(0.3905)
Run 3	Pollution	−3.6888	−3.0910	0.2124	2.8382	−4.7675	−1.4919
		(0.2396)	(0.2475)	(0.9463)	(0.2151)	(0.1249)	(0.5411)
	Intercept	−11.2665	−10.8154	0.9871	9.7956	−14.7805	−5.0767
		(0.1885)	(0.1447)	(0.9278)	(0.2176)	(0.1441)	(0.5218)
Run 4	Dust	**3.5701**	**3.9113**	−1.2561	−2.2644	−1.2189	**−2.6559**
		(0.0495)	**(0.0111)**	(0.4858)	(0.0805)	(0.3464)	**(0.0166)**
	Intercept	17.1018	17.7631	−5.0088	−9.2352	−3.5910	−9.0686
		(0.0784)	(0.0304)	(0.5281)	(0.1031)	(0.4407)	(0.0237)

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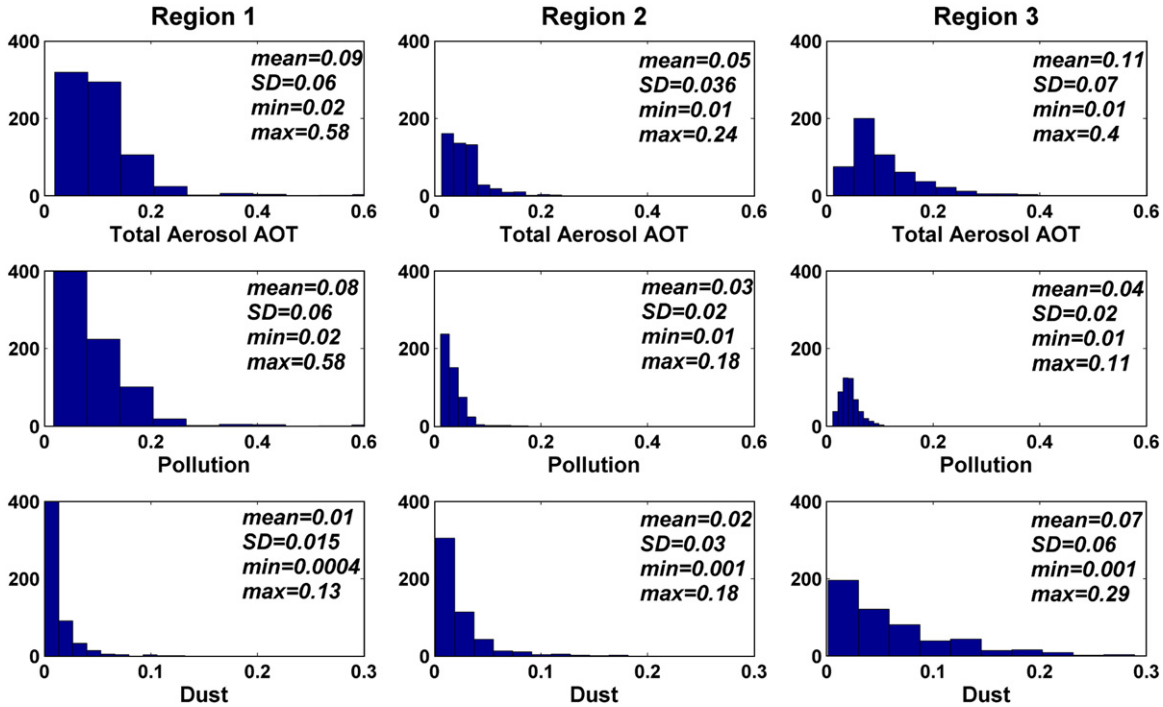

Fig. 6. The distribution of the variables: total aerosol AOT (TAOT), pollution and dust in each region. From left to right: the columns are for regions 1, 2 and 3.

carries with it always well correlated amounts of pollution. Pollution that can occur without dust does not produce a significant signal in regions 2 and 3; therefore, relating the indicated effect in region 2 to pollution itself would also be incorrect. The conclusion is that each aerosol on its own cannot explain dVmax variability because all aerosols are inter-correlated. In region 1, a significant positive relation of dust with dVmax was found despite the very small values of the dust mean AOT, which, according to the aerosol distribution in each region (presented in Fig. 6) is 7 times smaller than in region 3. This statistical relationship evoked further statistical analysis to explore the possible microphysical impact of aerosols which might be region dependent.

The TAOT coefficient estimates are similar for region 3 and for all the regions (Table 2, lead time 36 h). Therefore, it appears that region 3 is the main contributor to the overall coefficient estimate of the TAOT variable of run 1, when considering all the regions. A hypothesis which could explain the statistical significance of region 3 and the lack of significance in region 1 is that the TCs in the eastern Atlantic are in their initial and developing stages while farther west, in regions 2 and 1, TCs are in their mature and dissipating stages. Therefore, in region 3, the TC intensity is more susceptible to increased aerosol quantities. Zhang et al. (2009) simulated that when CCN is added to the initial environment in which the TC develops the aerosols had a larger impact on the TC intensity compared to when added just to the outer rainbands in the mature stage.

In order to examine this hypothesis on the data set of this study, a new variable was calculated named "age index". Each TC in the data set has a different number of data points. A consecutive discrete variable was created in the data set which associated each data time step a number. Its value starts out in 1 for each TC and its length is the number of data points in each TC. This was then divided by the total amount of data points available for each TC, creating a new variable which associated to each data point, relatively, what life stage the TC is in, the "age index" variable. When this variable equals 100%, it is associated to the last data point available of that TC and numbers close to 0 are associated with data points at the beginning of the TC life. The notion that regions 2 and 3 contain TC data that is associated to the earlier stages in a TC lifecycle is supported in Table 8 which shows the "age index" descriptive statistics in each region. According to the percentiles value of the age percentage in each region, it is evident that TCs in region 3 are younger than in regions 2 and 1.

Table 8
The descriptive statistics of the "age index" in each region, including the mean value of the age index with the addition of one standard deviation (SD). Also shown are the values of the three different percentiles of the age index, the 25th percentile (25%), the 50th percentile (50%) and the 75th percentile (75%).

Statistic	Region 1	Region 2	Region 3
Mean ± SD	51.2 ± 24.6	46.5 ± 24.5	46.6 ± 32.5
25%	31.5	28.01	16.4
50%	53.5	45.3	40
75%	71.3	64.3	78.4

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In order to get a clearer picture with regard to TC susceptibility to aerosols as a function of the TC life stage, the data was divided into three groups according to the age percentage variable. Group one contained the age percentage value between 1% and 33%, group 2, 34%–66% and group 3 67%–100%. The results are presented in Table 9. According to these results, the GFDL model forecast errors are less responsive to this division compared to SHIPS. For SHIPS, only in the earlier stages of the TC, was its intensity susceptible to aerosol decaying effect while in the two later stages there were no significant associations between the forecast errors and the aerosols. For GFDL, none of the groups was found to have a significant association with aerosols, however, in group 2, which contained the age percentage of 34%–66%, the coefficient estimate was the most significant.

From this analysis it may be indicated that TC intensity is in fact more susceptible to aerosols in its earlier stages in comparison to its later stages.

4. Discussion, summary and conclusions

This study uses for the first time forecast values from two independent TC forecast models to separate the aerosols from meteorological factors. The statistical results in this study support the hypothesis that CCN aerosols weaken TC intensity. According to the hypothesis, the microphysical effects of the CCN aerosols invigorate the clouds at the periphery of the storms and induce evaporative cooling at the lower levels, which weaken the airflow into the eyewall and hence reduce the maximum wind speeds (Rosenfeld et al., 2007; Zhang et al., 2009).

These findings underline the importance of precipitation forming and evaporating processes in TC clouds, especially during the developing stages of the TC. This accentuates the need to simulate the cloud aerosol interactions and the dynamic responses for obtaining additional improvements in TC prediction models. The dynamic responses, especially through the modification of the cold pools, might also be important in the process of the TC eyewall replacement, which is a cause for rapid and poorly predicted changes in the TC intensities (Houze et al., 2007).

This study showed that aerosols can explain variability of TC prediction errors. Therefore, incorporation of the aerosol effects in TC prediction models might increase their accuracy. A proper formulation of the effects of aerosols in TC prediction models requires additional research involving in situ measurements of aerosols and cloud properties, to be conducted with the TC monitoring airplanes in storms ingesting air masses with various aerosols.

Table 9
The multiple regression total aerosol AOT (TAOT) coefficients and their significance levels for explanation of variability in dVmax [knots] in each "age" group. The values are for GFDL and SHIPS predictions of 36 h lead time. The numbers in bold are statistically significant on a 0.05 level.

Age percentage	Explanatory variable	GFDL	SHIPS
till 33%	N		
	TAOT	−3.8973	**−4.5633**
		(0.1667)	**(0.0133)**
	Intercept	−12.059	−15.2688
		(0.1097)	(0.002)
33%–66%	N		
	TAOT	−4.9418	−3.1406
		(0.0839)	(0.193)
	Intercept	−12.346	−6.3566
		(0.1307)	(0.3563)
67%–100%	N		
	TAOT	−2.5208	0.6602
		(0.2803)	(0.7627)
	Intercept	−7.9026	0.7733
		(0.224)	(0.8992)

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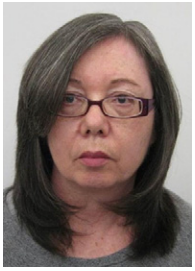
Michal Clavner is a post graduate student of the Institute of Earth Sciences, The Hebrew University of Jerusalem. Her M.Sc study is the basis of this manuscript and goes by the same title.



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