The Influence of Shallow Convection on Tropical Cyclone Track Forecasts

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ABSTRACT

Accurate tropical cyclone (TC) track forecasts depend on having skillful numerical model predictions of the environmental wind field. Given that wind and temperature are related through thermal wind balance, structural errors in the processes that determine the tropical temperature profile, such as shallow convection, can therefore lead to biases in TC position. This paper evaluates the influence of shallow convection on Advanced Hurricane Weather Research and Forecasting Model (AHW) TC track forecasts by cycling an ensemble data assimilation during a 1-month period in 2008 where cumulus convection is parameterized on the coarse-resolution domain using the Kain–Fritsch scheme or the modified Tiedtke scheme, which contains a more appropriate treatment of oceanic shallow convection. Short-term forecasts with the Kain–Fritsch scheme are characterized by a 1-K, 700-hPa temperature bias over much of the western Atlantic Ocean, which is attributed to a lack of shallow convection within that scheme. In turn, the horizontal gradients in this temperature bias are associated with wind biases in the region where multiple TCs move during this period. By contrast, the Tiedtke scheme does not suffer from this temperature bias, thus the wind biases are smaller. AHW forecasts initialized from the data assimilation system that uses the Tiedtke scheme have track errors that are up to 25% smaller than forecasts initialized from the data assimilation system that uses Kain–Fritsch.

1. Introduction

Over the past 20 years, there has been a steady decrease in tropical cyclone (TC) position errors at nearly all lead times (e.g., Rappaport et al. 2009). This reduction in error is often attributed to a combination of improved initial conditions through better data assimilation techniques and additional observations (e.g., Aberson 2010), but also to improved model physics and numerical techniques (e.g., Bender et al. 2007; Hogan and Pauley 2007).

The TC track is largely determined by the large-scale wind field (e.g., George and Gray 1976) and the advection of planetary vorticity by the TC circulation (e.g., Holland 1983). In particular, previous work has shown that TC position most strongly correlates with the 500–700-hPa winds (e.g., Chan and Gray 1982); therefore, systematic or random errors in the wind field within this layer can degrade track forecasts. Moreover, temperature and vertical wind shear are linked via thermal wind balance; therefore, it is likely that any systematic bias in thermodynamic fields will be reflected in the winds.

Away from the intertropical convergence zone (ITCZ), the vertical profile of temperature and moisture is mainly determined by the balance of broad, but weak subsidence, longwave cooling, shortwave warming, and both deep and shallow convection (e.g., Yanai et al. 1973; Arakawa and Schubert 1974; Betts 1986). Shallow convection is the process whereby cumulus clouds that are not deep enough to produce precipitation transport air from the mixed layer across the boundary layer inversion, which results in the upward transport of moisture and downward transport of heat. This mixing has significant influence on the boundary layer depth, lower-tropospheric temperature, and winds (e.g., Bretherton et al. 2004; Kain 2004; Wang et al. 2004). Although shallow convection has received considerable attention...
with respect to its impact on simulating stratocumulus clouds, particularly over the Pacific Ocean (e.g., Bretherton et al. 2004; Wang et al. 2004; de Szoeke et al. 2006), other studies have shown this process is an important component of the Madden–Julian oscillation (e.g., Johnson et al. 1999; Benedict and Randall 2007), and other convectively coupled equatorial waves (e.g., Straub and Kiladis 2002; Kiladis et al. 2009).

In addition, other studies have shown the importance of shallow convection on TC intensity and, to a lesser extent, track. Emanuel (1989) used an axisymmetric model to show that low precipitation efficiency clouds (i.e., shallow convective clouds) prevented overheating in the outer regions of a TC and vortex weakening during cyclogenesis. Moreover, Zhu and Smith (2002) found that shallow convection within a simple model acts to reduce the deep convective mass flux and buoyancy, thereby reducing the TC intensification rate. O’Shay and Krishnamurti (2004) demonstrated that adding shallow convection to a global model produced in incremental improvement in TC track during two recurving TCs. Recently, Han and Pan (2011) evaluated several improvements to the National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS), which included the treatment of shallow convection. Their results indicate that this new physics package led to reduced tropical cyclone track errors, which they attributed to better wind profiles.

This study expands upon Han and Pan (2011) by evaluating how shallow convection influences TC track forecasts within a cycling data assimilation coupled to the Advanced Hurricane Weather Research and Forecasting Model (AHW; Davis et al. 2008) during a 1-month period characterized by TCs of various intensity (Fay, Gustav, Hanna, and Ike), all of which either made landfall or threatened the continental United States (Fig. 1). The data assimilation setup is similar to Torn (2010) and is summarized below; the interested reader is directed to Torn (2010) for greater detail on the methods.

Both the data assimilation system and 4-km nested forecasts (described below) use version 3.3 of the Advanced Research version (ARW) of the Weather Research and Forecasting Model (WRF) (Skamarock et al. 2005) with 36 vertical levels up to 20 hPa and the modifications for hurricanes described in Davis et al. (2010). This implementation of WRF has the following components: WRF 6-class microphysics scheme (Hong et al. 2004), Rapid Radiative Transfer Model (RRTM) longwave radiation (Mlawer et al. 1997), Goddard shortwave scheme (Chou and Suarez 1994), Yonsei University (YSU) boundary layer scheme (Hong et al. 1997), Noah land surface model (Ek et al. 2003), and either the Kain–Fritsch cumulus parameterization (Kain and Fritsch 1993), or modified Tiedtke scheme (Zhang et al. 2011). All forecasts are run over a fixed 36-km domain that includes the entire Atlantic basin (shown in Fig. 1). In addition, the data assimilation system employs 12-km moving nest(s) of size 1600 km × 1600 km that follow any system designated as an INVEST or TC by the National Hurricane Center (NHC). The movement of these nested domains is determined based on the system’s motion over the previous 6 h. Once NHC stops tracking a particular

Fig. 1. Extent of the 36-km domain used in these experiments. The thin solid lines are the best-track positions of Fay (F), Gustav (G), Hanna (H), and Ike (I). The thick solid box denotes the area over which the temperature tendencies are calculated for Fig. 5, while the dashed solid box shows the rawinsonde verification area for Fig. 2. The dots denote the location of rawinsonde stations used in Fig. 2. Latitude and longitude are shown every 10°.

2. Model and data assimilation setup

A 96-member analysis ensemble is generated each 6 h by cycling an ensemble data assimilation over a 1-month period (0000 UTC 12 August–0000 UTC 14 September 2008) that was characterized by TCs of various intensity
system, the 12-km moving nest is removed in the cycling assimilation system. This strategy allows for greater resolution near the TC while still maintaining a large enough domain to cover the entire basin.

Observations are assimilated on both the 36- and 12-km nested domains from Automated Surface Observing System (ASOS) stations, ships, buoys, rawinsondes, the Aircraft Communications Addressing and Reporting System (ACARS), cloud motion vectors (Velden et al. 2005), and the Constellation Observing System of Meteorology (COSMIC) global positioning system (GPS) refractivity profiles (Anthes et al. 2008) using the Data Assimilation Research Testbed (DART; Anderson et al. 2009), which is an implementation of the ensemble adjustment Kalman filter (Anderson 2001). In addition, this system uses any dropsonde deployed within 1 h of the analysis time that is at least 100 km from the center of the TC. This distance criterion was employed because the 12-km domain is not sufficient to resolve features sampled by dropsondes near the eyewall. NHC TC advisory position and minimum SLP are also assimilated using the technique outlined by Chen and Snyder (2007), except that the center is determined from the maximum in 800-hPa circulation. Observation preprocessing is done using the methods outlined in Torn (2010) and observation errors are taken from NCEP statistics, except for TC position and minimum SLP, which are taken from Torn and Snyder (2012).

Sampling errors due to using a finite-sized ensemble are addressed via covariance localization and inflation techniques. The covariances are localized using Eq. (4.10) of Gaspari and Cohn (1999) where the value reduces to zero, 2000 km in the horizontal and two scale heights in the vertical from the observation location. In addition, the horizontal and vertical covariance length scales are reduced whenever there are more than 1600 observations within the localization ellipsoid as is described in Torn (2010). Covariance inflation is achieved using the adaptive technique of Anderson (2009), where the inflation factor is damped by 10% at each assimilation time and the inflation standard deviation is fixed at 0.6.

Ensemble initial and lateral boundary conditions are generated using the fixed-covariance perturbation (FCP) technique described in Torn et al. (2006), which produces ensemble perturbations by drawing random perturbations from the NCEP error covariances contained in the WRF-Variational (VAR) system (Barker et al. 2004). The initial ensemble is then generated by multiplying the state perturbation by 1.7 and adding it to the 24-h NCEP GFS forecast valid 0000 UTC 12 August 2008, which is 84 h prior to the genesis of Fay and allows the ensemble to have little memory of the initial perturbations by genesis time. Ensemble lateral boundary conditions are produced in a similar manner as the initial ensemble, but where the perturbations are scaled by 1.0 and the ensemble mean is the 6-h NCEP GFS forecast valid at the appropriate time.

During each analysis time with a TC, a 4-km resolution deterministic forecast is integrated to 120 h for each TC with initial conditions taken from a single member of the analysis ensemble at the appropriate time. The initial conditions for this forecast are determined by finding the analysis ensemble member that minimizes the following cost function that measures how close the analysis position and minimum SLP are to the ensemble-mean values:

\[
J(n) = \left( \frac{\text{Lat}_n - \overline{\text{Lat}}}{\sigma_{\text{Lat}}} \right)^2 + \left( \frac{\text{Lon}_n - \overline{\text{Lon}}}{\sigma_{\text{Lon}}} \right)^2 + 2 \left( \frac{\text{MSLP}_n - \overline{\text{MSLP}}}{\sigma_{\text{MSLP}}} \right)^2 .
\]

where Lat$_n$, Lon$_n$, and MSLP$_n$ are ensemble member n’s estimate of the TC latitude, longitude, and minimum SLP; \(\sigma\) is a climatological normalizing constant (0.15° for latitude and longitude, 4 hPa for minimum SLP); and the overbar indicates the ensemble mean of that quantity. This forecast uses the 36- and 12-km domains from the cycling data assimilation system with an additional 4-km nest (800 km \(\times 800\) km) centered inside the 12-km domain; the 4-km domain does not employ a cumulus parameterization. Ocean mixed layer depths are specified using the approach outlined in Davis et al. (2010). This process is repeated for each TC present at that particular initialization time, so that multiple forecasts are generated during times with more than one TC. Lateral boundary conditions for this forecast are taken from the GFS forecast initialized at the same time. Table 1 gives the forecast initialization times for each TC.

### Table 1. Forecast initialization times for each of the TCs studied here.

<table>
<thead>
<tr>
<th>Storm</th>
<th>Dates</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fay</td>
<td>1200 UTC 15 Aug–0000 UTC 27 Aug</td>
</tr>
<tr>
<td>Gustav</td>
<td>0000 UTC 25 Aug–0000 UTC 9 Sep</td>
</tr>
<tr>
<td>Hanna</td>
<td>0000 UTC 28 Aug–0000 UTC 7 Sep</td>
</tr>
<tr>
<td>Ike</td>
<td>0600 UTC 1 Sep–0600 UTC 14 Sep</td>
</tr>
</tbody>
</table>

3. **Cycling errors**

Prior to showing the impact of these two cumulus parameterizations on TC track and intensity forecasts, this section evaluates the systematic biases in 6-h forecasts of the temperature and wind field in the region.
where the TCs traverse during this period. The verification performed here uses 6-h forecasts because analyses have already incorporated the observations used in the verification, while longer lead times are characterized by larger random errors, which can make it difficult to isolate particular model errors.

a. Kain–Fritsch experiment

Figure 2 shows the RMS error and bias in 6-h ensemble-mean and GFS forecasts against rawinsonde observations within the box shown in Fig. 1. Given the long cycling period in these experiments, any biases should reflect a systematic model error. For zonal wind, there is an easterly wind bias below 300 hPa, with the largest values around 850 hPa. Moreover, the RMS error in this layer is 15% greater than the 6-h GFS forecast. In addition, this area is characterized by an up to 1-K temperature bias between 400–850 hPa and a ~0.3-K bias below that (Fig. 2b). This profile suggests that the boundary layer is systematically too cold, while the free troposphere is too warm, which is associated with larger RMS errors relative to GFS. Figure 3, which shows the time evolution of the 700-hPa temperature bias, suggests that this error quickly develops and maintain itself within the assimilation system. Over the first 5 days, the bias increases from nearly zero to greater than 1 K, then remains fairly consistent thereafter.

Given the lack of a comprehensive rawinsonde network in oceanic regions, it is difficult to establish the spatial extent of this particular warm bias. Moreover, since 6-h GFS temperature forecasts showed minimal biases when compared to rawinsondes, we compare the time-averaged 6-h ensemble mean forecast fields from the AHW data assimilation system against time-averaged 6-h GFS forecasts over the same period. As with rawinsonde observations, any difference between the two is likely related to a systematic bias in the AHW since GFS has smaller wind and temperature errors with respect to rawinsondes. Indeed, Fig. 4a indicates that the 6-h AHW forecasts are on average 1 K too warm over much of the western Atlantic basin, with the largest differences roughly collocated with the highest SSTs. Moreover, the western Atlantic and Caribbean are characterized by up to 2 m s\(^{-1}\) wind biases, which appear to align with the gradients in the

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2 The 1000-hPa bias consists of fewer locations and times; thus, it is ignored here.
temperature bias (Fig. 4b); therefore, it is possible that the wind biases are related to the temperature biases through thermal wind balance.

The validity of the aforementioned hypothesis is evaluated by computing the wind bias that would be in thermal wind balance with the time-average AHW 6-h temperature bias (computed with respect to time-average GFS 6-h forecasts). In particular, the wind bias is determined by integrating the thermal wind balance equation from 950 to 700 hPa, using the horizontal gradient in temperature bias, rather than gradients in absolute temperature, at 50-hPa intervals with the 950-hPa wind bias as the boundary condition for the wind bias. For grid points where 950 hPa is below ground, the integration starts from the first pressure level above ground. In addition, the calculation is not performed for grid points within 10° of the equator since geostrophic balance is not a strong constraint at these latitudes.
Although some differences exist near land, there is generally good agreement between the actual 700-hPa wind biases and the wind bias that is in thermal wind balance with the lower-troposphere temperature biases (Fig. 4c). In particular, the wind bias determined through thermal wind balance more or less captures the actual 700-hPa wind bias in the Gulf of Mexico, much of the Caribbean, off the East Coast of the United States, and in the eastern Atlantic. As a consequence, there appears to be a strong relationship between the temperature and wind errors, thus it is worth investigating why the model is producing this temperature bias over a large spatial area.

The physical processes responsible for this temperature bias are evaluated by generating a deterministic AHW forecast on the 36-km domain initialized at 1200 UTC 12 August where the initial conditions and lateral boundary conditions are the operational GFS analyses, which do not reflect the temperature biases seen previously. Figure 5 shows the hourly temperature tendency profiles averaged over the first 48 h of the simulation within the western Caribbean box shown in Fig. 1. This box is chosen because it is within the region of large 700-hPa bias with respect to GFS in Fig. 4a, has nearly zero horizontal temperature gradients, and is characterized by benign sensible weather during this 2-day period. As a consequence, the temperature tendency profile should reflect the process responsible for this temperature bias, rather than transient weather systems.

As might be expected for a quiescent tropical profile, the temperature tendency through much of the column is dominated by the sum of longwave radiation, shortwave radiation, and subsidence warming, with boundary layer mixing being important below $\sigma = 0.90$ (Fig. 5a). In addition, there is $<0.5$ K day$^{-1}$ warming throughout the column due to the cumulus parameterization that is maximized just below $\sigma = 0.90$. Some of this positive cumulus tendency is being offset by a negative temperature tendency associated with the microphysics scheme, which suggests the model is trying to produce grid-scale clouds at the boundary layer top, but they are evaporating. The net temperature tendency is positive between 0.60 $\leq \sigma \leq$ 0.85 and negative below that, which suggests the model is not adequately mixing higher potential temperature air from the free troposphere into the boundary layer. Most models account for this process through parameterized shallow convection, thus the results here suggest that this process is not being simulated properly.

It is worth noting that the version of the Kain–Fritsch parameterization used here contains shallow convection; however, it appears that it is formulated toward shallow convection over land, rather than ocean. In this scheme, shallow convection occurs when all of the conditions for deep convection have been met, except that the cloud model produces an updraft that does not meet the minimum cloud depth (Kain 2004). More importantly, the scheme does not trigger when there is grid-scale subsidence at the lifted condensation level (LCL), unless the layer is superadiabatic, which is rarely observed over the ocean. Moreover, some of the tunable parameters associated with shallow convection were adjusted to reduce tendencies over land during convective episodes (Kain 2004).

### b. Tiedtke experiment

Given the inherent limitations in the Kain–Fritsch scheme’s ability to simulate shallow convection over tropical oceans, the cycling experiment is repeated with the modified Tiedtke scheme (Zhang et al. 2011). In this scheme, shallow convection is parameterized by assuming
that the moisture flux through the cloud base is equivalent to the surface moisture flux, thus making it appropriate for tropical oceans (Tiedtke 1989), even in hurricane-force wind conditions (e.g., Drennan et al. 2007; Zhang et al. 2009). All other model and data assimilation settings are identical to the Kain–Fritsch experiment described above, so that the only differences between this experiment and the previously described results can be attributed to the difference in cumulus schemes and in particular the treatment of shallow convection.

Whereas the AHW model with Kain–Fritsch shows large temperature biases at 700 hPa, the cycling experiment with the Tiedtke has lower errors with respect to rawinsondes. Figures 2b and 3 show that the 6-h, 700-hPa temperature forecast bias using the Tiedtke scheme is −0.4 K, compared to 0.9 K with the Kain–Fritsch scheme and the RMS error is 0.3 K smaller between 600–850 hPa. Moreover, the zonal wind bias between 500–850 hPa is roughly 50% smaller in the Tiedtke experiment compared to running the data assimilation system with Kain–Fritsch cumulus.

The reduced temperature and wind biases are also evident in the comparison with respect to GFS 6-h forecasts. Throughout much of the Atlantic basin, the temperature bias is less than 0.4 K, while the 700-hPa wind bias north of the Caribbean islands, Gulf of Mexico, and along the East Coast of the United States is roughly 50% smaller in the Tiedtke experiment than the Kain–Fritsch experiment (Figs. 4d,e). The reduced wind biases should benefit TC track forecasts approaching the North American landmass since the winds in this layer have been shown to have the strongest correlation with TC motion (e.g., Chan and Gray 1982); this hypothesis is evaluated in the next section.

The impact of shallow convection on the previously observed 700-hPa temperature bias is further demonstrated by evaluating the temperature tendencies in an AHW forecast that uses the Tiedtke scheme and comparing to a forecast that uses Kain–Fritsch. Whereas the AHW with the Kain–Fritsch cumulus scheme is characterized by 1.7 K day$^{-1}$ net warming near $\sigma = 0.7$, the net temperature tendency is much smaller when using the Tiedtke scheme (Fig. 5b). Moreover, the Tiedtke scheme itself is producing cooling between 0.70 $\leq \sigma \leq$ 0.90, with warming below that, which is the expected result of shallow convection and the microphysics scheme is largely inactive.

To confirm that shallow convection is responsible for the improved net temperature tendency, we repeated the diagnostic forecast, but turned off shallow convection within the Tiedtke scheme (Fig. 5c). During this 48-h forecast, the cumulus scheme has little impact on the temperature profile, while the microphysics scheme shows a warming-above and cooling-below heating profile that is more characteristic of subtropical stratocumulus clouds (e.g., Zhang et al. 2011). Without shallow convection, the model cannot vertically advect the water evaporating from the ocean surface, thus the model produces shallow grid-scale clouds that drizzle at a rate of 1 mm day$^{-1}$. Overall, these results suggest that the Tiedtke scheme and in particular its shallow convection formulation allow the model to produce a more realistic large-scale temperature and wind fields.

4. Forecast influence

To quantify the value of having proper treatment of oceanic shallow convection on TC track forecasts, we produced deterministic track forecasts from the analyses that used both the Kain–Fritsch and Tiedtke schemes over each of the times listed in Table 1 (159 forecasts). In these forecasts, the 36- and 12-km domains used the same cumulus scheme as was used in the data assimilation system. All forecasts are verified against NHC best-track information during times when the system was at least a tropical depression.

Figure 6a indicates that the forecasts that use the Tiedtke scheme are characterized by a 25% reduction in track error compared to forecasts that use Kain–Fritsch beyond 48 h. These differences are statistically significant at the 90% confidence level based on a bootstrap resampling of the track error distribution with 10 000 realizations. It should be noted that the track error differences at days 4–5 are equivalent to a 1-day gain in track skill. This difference is fairly large considering that the only difference between the two forecasts is the cumulus scheme.

The forecasts with the Tiedtke scheme are also characterized by lower position biases (Fig. 6b). The Kain–Fritsch forecasts show a westerly position bias that increases with time at a roughly constant rate (roughly 80 km day$^{-1}$ over all forecast hours). By contrast, the Tiedtke forecasts have a more northward position bias and the magnitude of the bias is smaller than the Kain–Fritsch forecasts. Much of the northward-directed bias in the Tiedtke forecasts results from Hanna not making a looping track along the coast of Hispaniola (the Kain–Fritsch forecasts contain the same bias). In contrast, the forecasts of Ike are characterized by a strong westward bias in the Kain–Fritsch forecasts, but not in the Tiedtke forecasts (not shown). Although the Tiedtke position bias may seem large, the biases are comparable in amplitude and direction to Geophysical Fluid Dynamics Laboratory (GFDL) model over the same set of cases (not shown).
Much of the improvement in the TC track forecasts for this set of forecasts can be attributed to the reduction in the 700-hPa wind biases documented in section 3. Previous work (e.g., Chan and Gray 1982) suggests that TC position strongly relates to the winds at this level, thus the winds often act as the steering flow for the TC. Recall from Figs. 1 and 4b that Fay, Hanna, and Ike move through the region characterized by a 700-hPa easterly wind bias of 1.0–1.5 m s$^{-1}$ in the Kain–Fritsch forecasts. In turn, this should translate into a westerly position bias that grows at a rate of 86.4–129.6 km day$^{-1}$. The hypothetical position bias computed from the wind bias is in fairly good agreement with the 80 km day$^{-1}$ growth rate in position bias in the Kain–Fritsch forecasts. By contrast, the Tiedtke forecasts have a much smaller easterly wind bias in the region where the TCs move through (cf. Fig. 4e); therefore, the lower westerly position bias observed in Fig. 6b is not surprising. Overall, these results suggest that the reduction in position error and bias can be attributed to improvements in the steering flow biases in the regions the TCs move through.

In addition to producing better track forecasts, the Tiedtke scheme also produces a slightly better intensity forecast. Figure 6c shows that the maximum wind speed errors with the Tiedtke scheme are smaller than the KF at all lead times, though the difference is statistically insignificant at most lead times. Investigation of the exact cause for this improvement is beyond the scope of this work; however, it is likely related to improved landfall timing in the Tiedtke forecasts.

5. Summary and conclusions

This study demonstrates the importance of proper treatment of shallow convection in producing accurate forecasts of TC track in the Atlantic basin. These results are obtained by cycling an EnKF data assimilation system over a 1-month period that is characterized by four landfalling TCs and generating up to 120-h, 4-km forecasts using a single member of this analysis ensemble.

*Fig. 6.* Mean absolute error in (a) TC track and (c) maximum wind speed in AHW forecasts that use the Kain–Fritsch (AHKF; solid) and Tiedtke (AHW4; dashed) cumulus convection on the outer two domains as a function of forecast hour for the dates listed in Table 1. Error bars indicate the 90% confidence bounds determined from bootstrap resampling, while the numbers along the bottom give the number of times. (b) The position bias as a function of forecast hour, with dots indicating the location each 24 h, with labels for the 48- and 96-h values.
Two different cycling experiments are performed: one where the assimilation and forecast system use the Kain–Fritsch cumulus parameterization on domains with resolution greater than 4 km and another where the modified Tiedtke scheme is used instead.

Cycling the AHW model with the Kain–Fritsch cumulus scheme leads to lower to middle-tropospheric temperatures that are warmer than both rawinsondes and 6-h GFS forecasts over much of the tropical western Atlantic basin, excessive easterly winds north of the Caribbean islands, and deficient easterlies over the southern part. These wind biases appear to be in near-thermal wind balance with the temperature bias. Diagnostic model simulations initialized from a GFS analysis indicate that the positive temperature bias results from the imbalance between subsidence warming, longwave cooling, and cumulus convection. In the tropical troposphere, the latter process mixes higher potential temperature air downward through the boundary layer inversion via shallow convection; however, that does not appear to be the case with Kain–Fritsch. Closer inspection of the Kain–Fritsch treatment of shallow convection suggests that the current configuration of this scheme is not appropriate for tropical oceans due to its triggering and parameter assumptions.

Repeating the data assimilation cycling with the Tiedtke cumulus scheme, which includes better treatment of oceanic shallow convection, leads to better agreement between the AHW 6-h wind and temperature forecasts with respect to both observations and short-term GFS forecasts. Much of the improvement can be attributed to the Tiedtke scheme producing shallow convection that mixes down the high potential temperature air just above the boundary layer, leading to a near-zero net temperature tendency over much of the column. Since the horizontal gradient in temperature bias is nearly zero, the wind biases are also reduced.

AHW forecasts initialized from analyses that cycle with the Tiedtke scheme produce a statistically significant improvement in TC track forecasts compared to AHW forecasts initialized from analyses that employ the Kain–Fritsch scheme. The smaller track errors in the Tiedtke forecasts are associated with lower westerly track biases during the first 72 h of the forecasts, which is consistent with the smaller easterly wind biases in the 6-h Tiedtke forecast. This result suggests that the proper treatment of shallow convection can be an important aspect of predicting TC track forecasts. As a consequence, any numerical forecast of TCs that uses a cumulus scheme on a coarser-resolution domain should make sure that parameterization can accurately simulate oceanic shallow convection.

We propose that computing short-term forecast biases against rawinsondes or global model analyses over small regions can be used in a wide variety of applications to diagnose persistent model biases. The proper diagnosis of these biases requires cycling the model of interest with observations over longer periods of time so that the systematic bias can emerge from random errors. Future work will involve using this approach to diagnose the the 2–3 m s\(^{-1}\) westerly wind bias between 10°–20°, which exists in both the Kain–Fritsch and Tiedtke experiments (Fig. 4). We hypothesize that this bias is related to the treatment of aerosol in the Saharan air layer (e.g., Dunion and Velden 2004) by the model’s radiation scheme, though additional tests are required to confirm this.

Moreover, this work underscores the need to employ physics packages that are appropriate for the given application, particularly when cycling with observations over long periods of time, or regional climate applications. Both of these applications are particularly sensitive to systematic model biases because the model cannot fall back onto a parent model’s gridded data, except through the lateral boundary conditions.

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REFERENCES

Bender, M. A., I. Ginis, R. Tuleya, B. Thomas, and T. Marchok, 2007: The operational GFDL coupled hurricane–ocean prediction...


