AGU PUBLICATIONS

Geophysical Research Letters

RESEARCH LETTER

10.1002/2016GL071236

Key Points:

- Seventy-two percent of Atlantic TCs have origins related to AEWs
- AEW EKE is related to Atlantic TC genesis on interannual timescales in the low levels, below where it is maximized
- AEW EKE is a better predictor of seasonal TC genesis on interannual time scales during weak-moderate EKE years

Supporting Information:

- Supporting Information S1
- Figure S1
- Figure S2
- Figure S3
- Figure S4
- Figure S5
- Figure S6
- Figure S7

Correspondence to:
J. O. Russell,
jorussel@ncsu.edu

Citation:
Russell, J. O., A. Aiyyer, J. D. White, and W. Hannah (2017), Revisiting the connection between African Easterly Waves and Atlantic tropical cyclogenesis, *Geophys. Res. Lett.*, *44*, 587–595, doi:10.1002/2016GL071236.

Received 20 SEP 2016
Accepted 24 DEC 2016
Accepted article online 29 DEC 2016
Published online 12 JAN 2017

Revisiting the connection between African Easterly Waves and Atlantic tropical cyclogenesis

James O. Russell[1], **Anantha Aiyyer**[1], **Joshua D. White**[1], **and Walter Hannah**[1]

[1]Department of Marine, Earth, and Atmospheric Science, North Carolina State University at Raleigh, Raleigh, North Carolina, USA

Abstract African Easterly Waves (AEWs) are the primary precursor for Atlantic tropical cyclones (TCs). We update the statistics on this relationship using reports from the U.S. National Hurricane Center. Sixty-one percent of TCs originate directly from AEWs. Indirectly, AEWs are implicated in the formation of an additional 11% of TCs. AEW activity is quantified by eddy kinetic energy (EKE). The correlation between seasonal mean EKE and TC genesis is maximized in the lower troposphere below the southern AEW storm track, instead of where the canonical AEW is maximized. Therefore, midlevel AEW activity is a poor predictor of TC genesis, whereas its lower tropospheric circulation exerts stronger control. In most seasons, AEW activity is supercritical, and therefore, EKE is only a controlling factor in seasons when the low-level EKE is weak. Predicting 1000–800 hPa EKE below the southern AEW track may be useful for seasonal TC prediction.

1. Introduction

African Easterly Waves (AEWs) are synoptic-scale disturbances that form over sub-Saharan Africa during the West African Monsoon season (June–October) [e.g., *Burpee*, 1972]. In seasonal mean dynamical fields (e.g., vorticity and eddy kinetic energy), AEW amplitudes are maximized along 12°N at 650 hPa and along 20°N at 925 hPa. These are often called the southern (mid-level) and northern (low-level) AEW tracks. AEWs propagate westward toward the Atlantic where they are the primary precursors of tropical cyclones (TCs) in the Atlantic Basin [*Landsea*, 1993; *Avila et al.*, 2000]. In this paper we aim to improve the understanding of this relationship between AEWs and TCs. Therefore, our first goal is to update statistics related to this relationship to include an additional 21 years (1995–2015) of data. To do this, we examine what we define as the *genesis number* (GN) and the *genesis fraction* (GF). These are the number of TCs that originate from AEWs and the fraction of TCs that originate from AEWs, respectively. These metrics measure the relative importance of AEWs as TC precursors.

Early attempts to quantify tropical cyclogenesis from AEWs were in a series of papers by Simpson and Frank during the late 1960s [*Simpson et al.*, 1968, 1969; *Frank*, 1970]. Using satellite imagery, they found that over 50% of TCs originated from AEWs. Later, *Avila and Pasch* [1992], often cited as the source for the GF [e.g., *Kiladis et al.*, 2006; *Schwendike and Jones*, 2010; *McCrary et al.*, 2014], showed that the GF was 0.57 for the period 1967–1990. This and subsequent studies [*Landsea*, 1993; *Avila and Pasch*, 1995; *Pasch et al.*, 1998; *Landsea et al.*, 1998; *Avila et al.*, 2000] used surface observations, upper air data, and satellite imagery to establish the origin of TCs. *Landsea* [1993] showed a GF of 0.58 for all TCs and 0.83 for intense hurricanes during 1967–1991. *Avila et al.* [2000] was the final study in the series of papers on the subject first authored by Avila and Pasch. This study reported a GF of 0.62 for the 31 seasons between 1967 and 1997. More recently, *Chen et al.* [2008] showed that the GF was 0.58 by backtracking AEWs between 1979 and 2006. This study used gridded reanalysis fields and differed in the methodology used by National Hurricane Center (NHC) forecasters in their annual reports. The preceding discussion shows that there is variability in the estimates of GF. In this study we update the statistics presented in *Pasch et al.* [1998]. The aim is to provide an up-to-date and more definitive response to the question "What fraction of TCs form from AEWs?".

We also update these statistics to examine a metric that we define as the *genesis efficiency* (GE). GE relates the strength of AEW activity over the East Atlantic and sub-Saharan Africa to the number of TCs that form from AEWs. Understanding GE is theoretically important for the understanding of tropical cyclogenesis and also in an operational sense, for statistical forecasting of seasonal TC activity.

In most studies, GE has been investigated by comparing counts of AEWs to the GN. *Avila et al.* [2000] compared the number of AEWs per season to the GN. They reported a mean count of 61 AEWs per year, out of which, on average 11 became tropical systems. *Thorncroft and Hodges* [2001] also studied this relationship but used a tracking algorithm on 15 years of reanalysis data. They noted that a positive correlation existed between the number of AEWs and the GN. In contrast when *Hopsch et al.* [2007] improved on the methods of *Thorncroft and Hodges* [2001], they showed that interannual variability of AEW activity is not associated with variations in GN. *Belanger et al.* [2010] showed that AEW frequency only weakly impacts TC frequency. They showed that around 25% of the total variance in TC activity was associated with the frequency of AEWs. *Agudelo et al.* [2011] quantified GE using AEW counts and showed that between 1980 and 2001, 14% of AEWs were associated with the formation of TCs and 3% with major hurricanes. They also showed that there was a marked interannual variability of the GE with a range of nearly 70%. Clearly, when examining GE by comparing the GN to AEW counts, there is a marked difference between the statistics presented. The general consensus from these studies is that there is a relationship, albeit likely weak, between TC genesis and AEW counts.

Recently, *Price et al.* [2015] examined GE from a standpoint that did not include the counts of AEWs, but instead on the convection associated with AEWs. They examined the areal coverage of cold cloud tops associated with AEWs and found that there was a correlation between coverage and tropical cyclogenesis. In this study, we also aim to investigate GE from a different perspective. Here we use seasonal average eddy kinetic energy (EKE) associated with AEWs. EKE has been shown to be a useful measure of AEW activity and has been used in a number of studies to examine AEWs [e.g., *Hsieh and Cook*, 2007; *Diaz and Aiyyer*, 2013]. From a seasonal perspective, the main advantage of EKE is that it quantifies both the strength and number of AEWs, rather than just the number or, an indirect measure of their strength (such as convection). Further, EKE calculations are easier to reproduce and suffer fewer limitations compared with relatively complicated methods and algorithms typically used to track AEWs.

In summary, the goals of this study are twofold: to extend and examine the statistics associated with GN and GF and to investigate GE from the standpoint of seasonally averaged EKE associated with AEWs.

2. Data and Methods

We surveyed NHC TC reports for the years 1995–2015 (NHC TC Reports, 2016, http://www.nhc.noaa.gov/data). Any tropical cyclone (this includes tropical depressions, storms, and hurricanes but does not include subtropical storms) in this data set contributed to the total number of tropical cyclones per season (TN) used in our study. A TC was defined as directly linked to an AEW if the NHC report stated that its primary incipient disturbance was a westward moving tropical wave that left the coast of Africa. Any TC that fell in this subset of the data contributed to the GN and genesis fraction of all TCs for that season (GF = GN/TN).

We also define a second category that we deem important, namely, the contribution number (CN) and contribution fraction (CF = CN/TN). This comprises all cases wherein the AEW was not the primary incipient disturbance but had a positive effect on TC formation. Such events include TC genesis from disturbances on the Intertropical Convergence Zone or upper level troughs, where an interaction with an AEW was identified in the NHC report as contributing to TC genesis. To our knowledge, this category has yet to be studied in detail likely because of the difficulty in identifying such events through objective tracking. However, we include this category as we seek to discuss the full implication of AEWs with regard to TC genesis.

We recognize here that NHC TC reports are subjective, and the statistics obtained may be biased in some way by the interpretation of NHC forecasters and our interpretation of the language used. However, we note that identification of GN and CN is made possible by the remarkably consistent and detailed language across 21 years of reports. We also use these reports for a number of reasons. First, they provide a level of consistency with the data presented in *Avila et al.* [2000]. The methods used in NHC TC Reports (2016, http://www.nhc.noaa.gov/data) and *Avila et al.* [2000] are similar (i.e., identification by experienced NHC forecasters using a variety of observations including satellite, surface, and upper air data). Further, for the 3 years of overlap between the data sets, GNs for tropical cyclones and hurricanes are similar, indicating that the data sets are comparable. Direct comparisons to *Avila et al.* [2000] are therefore possible. Second, observations across Africa and the Atlantic are sparse, and therefore, it is unclear whether studies that utilize model and reanalysis data are examining reality for individual waves. Large biases in reanalyses over West Africa are shown to be prevalent for individual cases by *Roberts et al.* [2015]. Third, AEWs are difficult to track using automated tracking algorithms in typical meteorological fields. *Thorncroft and Hodges* [2001] noted that weak AEWs are ignored by tracking algorithms and that AEWs can be double tracked as a result of reintensification.

In this study, we use EKE as a measure of AEW activity. It is calculated as

$$\mathrm{EKE} = \frac{1}{2}\left(u'^2 + v'^2\right) \tag{1}$$

where u' and v' represent the perturbation zonal and meridional components of the wind velocity. The perturbations are defined using a wave number-frequency filter [*Hayashi*, 1982] following the method of *Wheeler and Kiladis* [1999]. Filter parameters are set to 2–10 days for the periods and 10–40 for the wave numbers (approximately 1000–4000 km equivalent wavelength), and the waves are constrained to be westward propagating. These parameters give filtered perturbations representative of AEWs. Winds are obtained from the ERA-Interim reanalysis chosen for its advanced data assimilation system with respect to other reanalyses [*Dee et al.*, 2011]. Discrepancies with other reanalyses are discussed in the supporting information. While the reanalysis data may have significant biases for individual systems, we take a seasonal approach and consequently these data should be sufficiently accurate to diagnose the seasonal mean EKE. Seasonal averages are computed for July–September (JAS).

3. Genesis Fraction/Number

Our survey found that 216 of the total of 335 TCs (GF of 0.64) could be directly linked to AEWs between 1995 and 2015. In addition, a further 36 TCs (CF of 0.11) had origins that could be linked to AEWs. When these two categories are combined, approximately 75% of the total TCs during the 1995–2015 period have origins relating to an AEW. This equates to a yearly average GN of 10.3 and CN of 1.7 (Figure 1c). Therefore, out of an average of 16 TCs per year, 12 had origins related directly or indirectly to AEWs. This is a notably higher number/fraction of TCs than previously reported since the CN is taken into account here, where in most studies GN is only taken into account [e.g., *Landsea*, 1993; *Avila et al.*, 2000].

Figure 1a shows the GF and CF for all TCs by year. Data prior to 1995 was taken from *Avila et al.* [2000]. When the entire period shown in Figure 1 is considered, the average GF is 0.61. Figure 1a shows that there is a marked interannual variability in GF. It ranges from 0.25 in 1972 and 1997 (during which the onset of El Niño was occurring) to 0.93 in 1989 (during the decay of a La Niña). The GF has a standard deviation of 0.16 over 1967–1994 and 0.14 over 1995–2015. The large variability explains a lack of significant differences of GN and GF between the two data sets covering the periods 1967–1994 and 1995–2015, respectively. CFs vary from 0 to 0.22, with a standard deviation of 0.07, again indicating a large amount of variability from year to year.

For hurricanes (Figures 1b and 1d) between 1995 and 2015, the GF is higher than for all tropical cyclones at 0.71 (110 of 156 hurricanes). The CF is similar for hurricanes, at 0.1 indicating that 81% of hurricanes have their origins influenced by AEWs. These numbers equate to an average GN of 5.2 and CN of 0.8, resulting in a total of 6 out of an average of 7.4 hurricanes per season having origins influenced by AEWs.

The variability for hurricanes is higher than that for tropical cyclones with a standard deviation for the GF of 0.24. Year 1991 had a hurricane GF of 0, while 7 other years had a hurricane GF of 1.0. A similar picture is apparent for CF with a standard deviation of 0.14, many years having a CF of 0, and 2013 having a CF of 0.5. Again, the high variability means there are no significant differences between the two data sets.

4. Genesis Efficiency

As noted earlier, we use EKE instead of AEW counts to further examine the relationship between AEW activity and TC genesis. This provides a succinct and easily reproducible metric for describing the efficiency of TC genesis from AEWs.

4.1. Definition

In this study we define GE for each year as

$$\mathrm{GE} = \frac{\mathrm{GN}}{<\mathrm{EKE}>} \tag{2}$$

where $<\mathrm{EKE}>$ represents a nondimensional quantity defined as the seasonal mean EKE averaged over a defined atmospheric volume, divided by its long-term standard deviation. The volume encompasses the

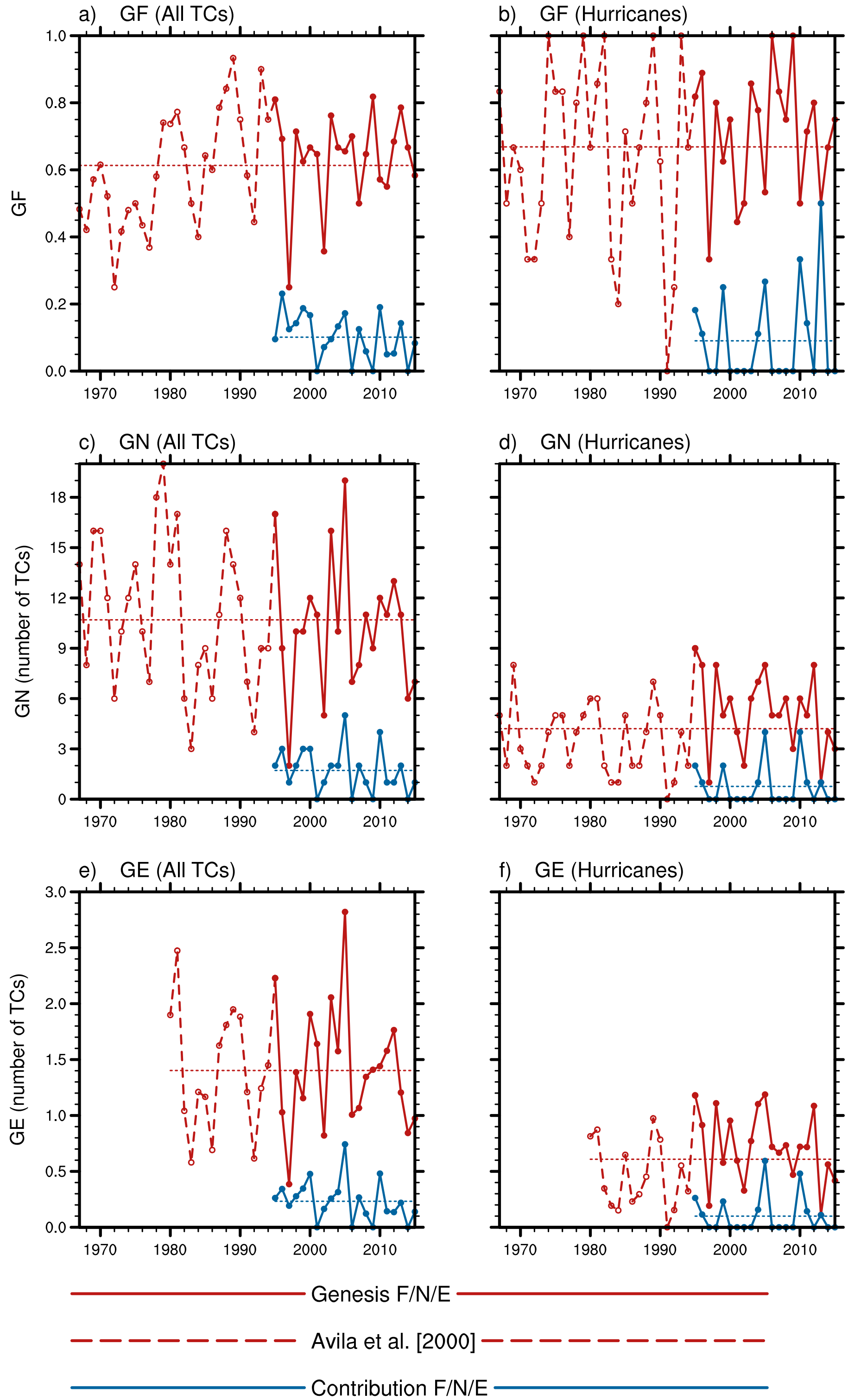

Figure 1. GF/GN/GE (red) and CF/CN/CE (blue) for (a, c, and e) all tropical cyclones and (b, d, and f) just hurricanes. Figures 1a and 1b show GF/CF, Figures 1c and 1d show GN/CN, and Figures 1e and 1f show GE/CE. Solid lines indicate data obtained from our survey of the NHC TC Reports (2016, http://www.nhc.noaa.gov/data). Dashed lines indicate data from *Avila et al.* [2000]. Mean GF/GN/GE are represented by the horizontal dotted lines.

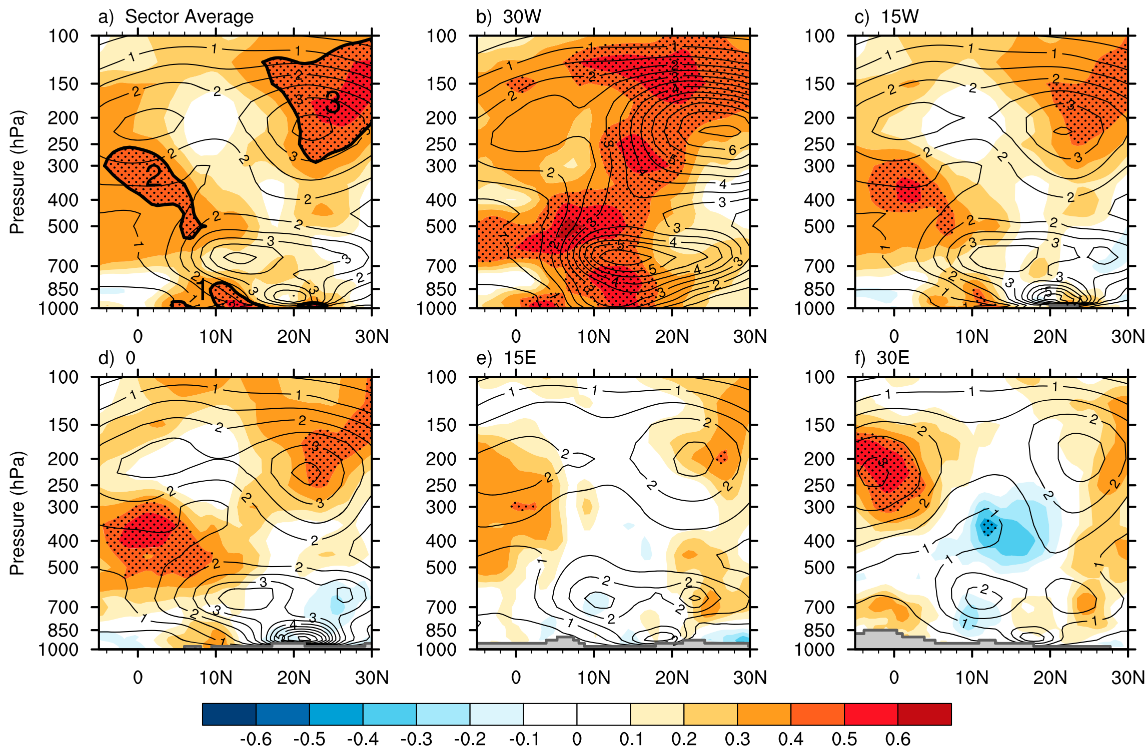

Figure 2. Latitude-height cross sections of the correlation between GN and seasonal mean EKE (filled) for (a) 30°W–30°E, (b) 30°W, (c) 15°W, (d) 0°, (e) 15°E, and (f) 30°E. Contours represent the seasonal mean EKE (J/kg), and stippling represents statistical significance of 95% for the correlations. Outlined areas with numbers represent specific statistically significant areas of correlation discussed in the text.

region between 20°W and 10°E, 8°N and 15°N, and 1000 hPa and 800 hPa. As discussed in the next section this region shows the highest correlation between AEW activity and GN.

Figure 1e shows the GE for all TCs from 1980 to 2015. The average GE for 1980–2015 is 1.4. However, GE varies from as low as 0.4 to as high as 2.4 during this period. For only hurricanes GE is lower (as expected), with an average of 0.6, and a range of 0–1.2. If we add the contribution efficiency to the genesis efficiency, the average for all TCs goes up by 0.3 to 1.7, while the average for just hurricanes goes up by 0.2 to 0.6.

4.2. Correlations

We next examine genesis efficiency by investigating the correlation between EKE and GN relative to seasonal mean EKE (Figure 2). Statistical significance for the correlations is calculated using a two-tailed Student's *t* test with a 95% confidence interval. Correlations rarely exceed 0.6 (a strong correlation) and a majority of the statistically significant correlations are between 0.4 and 0.6 (moderate correlation). These relatively low correlations indicate that TC genesis is governed by factors other than AEW activity such as ocean heat content, wind shear, and the large-scale circulation [*Gray*, 1984].

Figure 2a shows the mean EKE (contours) overlaid on the correlation (color filled) between GN and sector averaged (30°W–30°E) EKE. Three regions of significant correlation are (1) in the low levels, below the midlevel peak in EKE that represents the southern track of AEWs; (2) a region between 250 and 550 hPa south of the AEW track (near the equator); and (3) aloft between 300 and 100 hPa in association with a peak in the EKE centered on 25°N. These regions are outlined in Figure 2a. Surprisingly, there are no statistically significant correlations associated with the EKE maximum that represents the midlevel southern track and the low-level northern track AEWs.

Examining region 1 in more detail, this correlation only exists over West Africa, west of the Greenwich meridian as seen in Figures 2b–2d. Further, it grows stronger to the west, from 0.3 to 0.4 at the Greenwich meridian to 0.5–0.6 by 30°W (Figures 2d and 2b, respectively). *Price et al.* [2015] showed that convective activity in AEWs is related to TC genesis. That is likely reflected in the correlation with the low-level EKE in Figure 2a. This strengthening low-level correlation indicates the development of a near-surface circulation associated with the AEWs that could potentially serve as a TC precursor. The diabatic heating gradient due to moist convection associated with AEWs is strongest in the low levels, and positive PV generated by the gradient is likely a pathway for the low-level circulation [*Raymond and Jiang*, 1990].

Regarding region 2, we note that the strongest correlation from Figures 2c and 2d is over the Gulf of Guinea between 10°W and 10°E, a region where the AEW-related EKE is small. The physical mechanism behind this correlation is unclear. It may relate to the southern extent of AEWs although this is unlikely since it occurs above the peak EKE maximum representing AEWs. Alternatively, it may be related to waves on the tropical easterly jet (TEJ) with the same filter parameters as AEWs. There is also significant correlation associated with waves on the TEJ, east of the Gulf of Guinea over Central Africa (Figure 2f). It may be that these two regions of correlation are linked such that the TEJ affects AEW activity in these regions and that, in turn, may influence TC genesis.

Region 3 is associated with an area of EKE aloft that gets stronger to the west (Figures 2b–2d). This is likely associated with midlatitude intrusions into the subtropics and tropics that are advected westward in the tropical easterly flow (thus resulting in a westward propagating EKE anomaly) [e.g., *Roca et al.*, 2005]. Any possible dynamical links for the correlations in regions 2 and 3 though are out of the scope of this study and should be investigated in future work.

One final observation from Figure 2 is the statistically significant correlation throughout the column at 30°W. We note that since the circulation of a TC may project on the AEW-filtered EKE [*Aiyyer et al.*, 2012], it may be artificially enlarging the correlation over the ocean. However, the EKE in Figure 2b clearly indicates a peak at 650 hPa, whereas if this were dominated by TC EKE, we would expect to observe a near-surface peak with a deep, vertically stacked column of EKE. Further, less than 20% of TCs forming from AEWs during 1995–2015 originated east of 30°W. Therefore, we still believe this to represent the AEW EKE rather than TC EKE. The correlation between GN and AEW activity is higher over the ocean than over land. This is likely a reflection of the transformation of the AEW once it passes the coast and its importance for TC genesis.

4.3. Variability with EKE

We conclude our analysis by returning to further examine the first area of correlation, that which is most likely related to the AEWs. We use the bootstrapping method [*Wilks*, 2011] to further develop our understanding of this correlation. We first calculate the seasonal mean EKE for each year in the outlined area shown in the key at bottom left in Figure 3 (averaged between 20°W and 10°E). This provides us with 36 pairs (representing each year from 1980 to 2015) of GN and seasonal mean EKE associated with the statistically significant correlation below the mid-level AEW EKE maximum. We then randomly resample these pairs (with replacement) 100,000 times with 30 pairs in each new sample. In other words, by assuming that 1980–2015 is representative of our climate, we stochastically generated 30 year periods that represent a range of possibilities for this climate. We correlate GN and EKE for each sample and plot the correlation coefficient against the mean EKE for that sample. By doing this for all 100,000 resamples, a density plot is generated, as shown in Figure 3a.

This density plot is clearly oriented from high correlation and low EKE to low correlation and high EKE. Further, a linear least squares regression indicates a statistically significant negative relationship, albeit with only moderate correlation. We quantify this relationship by comparing the top 2.5% of these samples to the bottom 2.5% of these samples (i.e., those that are 2 standard deviations below and above the average EKE—shown in box and whisker plots in Figure 3a). The lowest 2.5% has a median correlation of approximately 0.6 with the upper 80% of the data having a correlation above 0.5. In contrast, the highest 2.5% has a median correlation of approximately 0.3 and the lower 80% of the data below 0.5. These two samples are significantly different with a p value less than 0.01 when tested using a Student's t-test.

We also carried out the same analysis on the region representing the peak of the AEW track (shown in the key at the bottom right of Figure 3b) and found that a similar negative relationship is present. Examining the lowest 2.5% of resamples for this region, there is a median correlation of approximately 0.4 with 75% of the resamples larger than 0.3. In contrast, the highest 2.5% of the resamples have a median correlation of 0.05 and a distribution that indicates the average correlation is not significantly different from a correlation of 0.

These results indicate that during seasons with low mean EKE (i.e., weaker waves as shown in Figure S3), AEW variability plays a larger role in modulating TC genesis. This should be expected since weaker TC precursors likely mean less TC genesis. However, during seasons with high mean EKE, AEW variability does not significantly impact TC genesis variability. This implies that for these high EKE seasons, AEW activity is supercritical

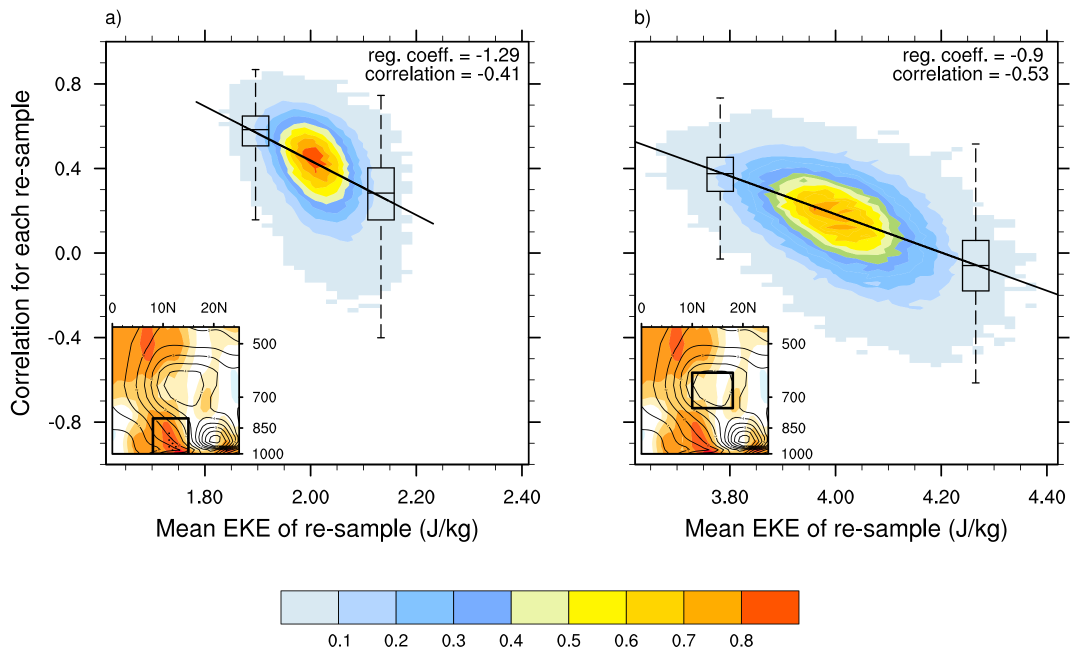

Figure 3. Density plots representing the percentage of subsamples in a 0.02 by 0.02 grid box. The correlation between mean GN and mean EKE for each subsample is represented on the *y* axis. (a and b) Figures in the bottom left are as in Figure 2 but for a sector average of the main AEW track, between 20°W and 10°E. The outlined areas in these subfigures show the area that the respective density plot represents. Lines represent the least squares regression with regression coefficient and correlation shown in the top right of each figure. Box and whisker plots represent the upper and lower 2.5% of data.

in the sense that waves are beyond a threshold intensity and their variability is no longer predictive of ensuing TC genesis. These results suggest that when AEW activity is high, AEW variability does not exert a major control on TC formation. On the other hand, when AEW activity is lower, AEW variability is a better control on TC variability.

4.4. Potential as a Seasonal TC Predictor

The relationship found in the previous section raises the potential that AEW activity (in particular the low-level EKE associated with AEWs) may be used in seasonal TC prediction. Typically, AEW activity is not a metric in most statistical or dynamical seasonal TC forecasts. A review by *Klotzbach et al.* [2012] of some of the primary operational dynamical and statistical seasonal TC forecasting methods showed that none of the forecasts reviewed incorporate a direct measure of AEW activity. Dynamical forecasts, such as that from the European Center for Medium-Range Weather Forecasts (ECMWF), track the number of TCs in one or multiple climate projection(s) and then bias correct using observations and a climatology from the model in question. Statistical forecasts such as those used by Colorado State University (CSU) and the NOAA Climate Prediction Center (CPC) use regression models based on sea surface temperatures, sea level pressure, and upper air height and wind fields. Given the results presented in this paper, some measure of AEW activity could be used in seasonal TC prediction.

One potential method could be to estimate the change in GN with low-level EKE using a regression model (i.e., using GE as calculated in section 4.1). This regression model would then only be valid at low to average EKE where the correlation between GN and EKE is high enough (i.e., at statistically significant EKE which is above 0.4) as shown in the previous section. Seasonal mean low-level EKE could be estimated by using medium to long range forecasts from operational models such as the Climate Forecast System [*Saha et al.*, 2006] and would therefore only be possible for statistical-dynamical hybrid models. However, developing such a regression model and validating it is reserved for future work as this is beyond the scope of the current study. Such a task would not only have to develop and test the regression model but also have to establish the accuracy of the climate projections used for estimating the low-level AEW EKE, understand how the AEW track is affected by other large-scale circulation changes such as ENSO, show that the inclusion of AEW EKE adds unexplained variance to predictors currently used in seasonal forecast models, and integrate the model of AEW activity with other metrics governing seasonal TC forecasts.

5. Conclusions and Implications

The aim of this study was twofold: first, to update the statistics on the relationship between AEWs and TCs and, second, to use that data to examine the efficiency of TC genesis through AEWs. We have addressed the first goal by extending the statistics presented in *Avila et al.* [2000] to include the period 1995–2015. Using nearly 50 years of TC data, we conclude that 61% of TCs originate directly from AEWs. During 1995–2015, a further 11% of TCs had origins that were indirectly linked to AEWs. When combined, assuming the CF was similar for the preceding period (i.e., 1967–1994), this indicates that up to 72% of TCs are positively influenced by AEWs during their genesis, a fraction that is substantially higher than previous studies [*Landsea*, 1993; *Avila et al.*, 2000], since these studies only reported the GF. The increased fraction emphasizes the importance of understanding and studying AEWs and their relationship to TCs.

To address our second goal, we used EKE to quantify AEWs and compared this to the GN. EKE provides a better means than counts to examine AEWs on a seasonal basis, as it provides a measure of both their intensity and number. Remarkably, there was little to no correlation between GN and either of the two EKE maxima that represent the AEW tracks. This is surprising since the consensus is that in some way, AEWs act as a seed for hurricanes [e.g., *Tyner and Aiyyer*, 2012], and therefore, one might have expected to see correlation between their maximum and the GN. Instead, there was a significant area of correlation between AEW EKE and the GN below the peak in EKE representing southern track AEWs. As discussed in section 4.2, this correlation is likely associated with convectively generated circulation in the low levels, as can be understood through PV dynamics. Further, there is little correlation at the mid-level maximum because other factors (such as convective available potential energy and shear) govern the strength of convection, while AEWs only organize convection such that the resulting low-level EKE is present on AEW space-time scales. The implication is that the variability of what can be considered the canonical AEW does not control TC genesis variability. Instead, the variability in the diabatically generated low-level circulation associated with the AEW is the determining factor. Of relevance here is the Marsupial paradigm [*Dunkerton et al.*, 2009] that attempts to bridge the TC genesis process between the synoptic-scale easterly wave and the mesoscale incipient TC vortex. Whether this diabatic circulation can be considered to be distinct from the parent wave or represents a hybrid vortex wave structure needs to be fully determined.

A stochastic examination of EKE and GN shows a strong relationship between low-level EKE and GN, but only when EKE is low. This suggests that the strength of AEW activity is not a limiting factor in seasons where the mean EKE is high. Additional reanalyses are examined in section 5 of the supporting information, and while one reanalysis corroborates this conclusion, another does not, casting some uncertainty on this result. Nonetheless, the results in this study highlight the potential for AEW activity conditioned on a suitable threshold (as measured by the EKE) to be used in seasonal TC forecasts.

One more implication that should be highlighted is the need to examine not just the canonical southern track and northern track when studying AEWs. AEWs have a three-dimensional structure [*Kiladis et al.*, 2006], and results here clearly show that the maxima in the respective tracks do not necessarily hold the most importance for the effect of AEWs on the surrounding climate. Therefore, studies examining the AEWs in future climate projections [e.g., *Skinner and Diffenbaugh*, 2014] should not only focus on the maxima in the respective tracks but also on the low levels below the southern track.

Acknowledgments

This work was supported by NSF grant 1433763. We thank the staff at the National Hurricane Center for their detailed and publicly available TC reports and the European Center for Medium-Range Weather Forecasting for free access to the ERA-Interim reanalysis. We also thank Phil Klotzbach, Christina Patricola, and an anonymous reviewer for their detailed and insightful reviews. National Hurricane Center Tropical Cyclone reports can be found at http://www.nhc.noaa.gov/data/#tcr. ERA-Interim reanalysis data can be found at http://apps.ecmwf.int/datasets/. National Aeronautics and Space Administration (NASA) Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) data can be found at https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/data_access/. National Center for Environmental Prediction (NCEP) and Department of Energy (DOE) Reanalysis 2 data are available from the Earth System Research Laboratory at https://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis2.html. International Best Track Archive for Climate Stewardship (IBTrACS) data are available at https://www.ncdc.noaa.gov/ibtracs/.

References

Aiyyer, A., A. Mekonnen, and C. J. Schreck III (2012), Projection of tropical cyclones on wavenumber-frequency-filtered equatorial waves, *J. Clim.*, *25*(10), 3653–3658.

Avila, L. A., and R. J. Pasch (1992), Atlantic tropical systems of 1991, *Mon. Weather Rev.*, *120*(11), 2688–2696.

Avila, L. A., and R. J. Pasch (1995), Atlantic tropical systems of 1993, *Mon. Weather Rev.*, *123*(3), 887–896.

Avila, L. A., R. J. Pasch, and J.-G. Jiing (2000), Atlantic tropical systems of 1996 and 1997: Years of contrasts, *Mon. Weather Rev.*, *128*(10), 3695–3706.

Agudelo, P., C. Hoyos, J. Curry, and P. J. Webster (2011), Probabilistic discrimination between large-scale environments of intensifying and decaying African Easterly Waves, *Clim. Dyn.*, *36*(7–8), 1379–1401.

Belanger, J. I., J. A. Curry, and P. J. Webster (2010), Predictability of North Atlantic tropical cyclone activity on intraseasonal time scales, *Mon. Weather Rev.*, *138*(12), 4362–4374.

Bosilovich, M. G., et al. (2015), MERRA-2: Initial evaluation of the climate, *NASA Tech. Rep. Ser. on Global Model. and Data Assimilation, NASA/TM-2015-104606*, NASA, Greenbelt, Md.

Burpee, R. W. (1972), The origin and structure of easterly waves in the lower troposphere of North Africa, *J. Atmos. Sci.*, *29*(1), 77–90.

Chen, T.-C., S.-Y. Wang, and A. J. Clark (2008), North Atlantic hurricanes contributed by African easterly waves north and south of the African easterly jet, *J. Clim.*, *21*(24), 6767–6776.

Diaz, M., and A. Aiyyer (2013), Energy dispersion in African easterly waves, *J. Atmos. Sci.*, *70*(1), 130–145.

Dee, D. P., et al. (2011), The ERA-Interim reanalysis: Configuration and performance of the data assimilation system, *Q. J. R. Meteorol. Soc.*, *137*, 553–597.

Dunkerton, T. J., M. T. Montgomery, and Z. Wang (2009), Tropical cyclogenesis in a tropical wave critical layer: Easterly waves, *Atmos. Chem. Phys.*, *9*, 5587–5646.

Frank, N. L. (1970), Atlantic tropical systems of 1969, *Mon. Weather Rev*, *98*, 307–314.

Gray, W. M. (1984), Atlantic seasonal hurricane frequency. Part 1: El Niño and 30 mb quasi-biennial oscillation influences, *Mon. Weather Rev.*, *112*, 1649–1668.

Hayashi, Y. (1982), Space-time spectral analysis and its applications to atmospheric waves, *J. Meteorol. Soc. Jpn.*, *60*, 156–171.

Hopsch, S. B., C. D. Thorncroft, K. Hodges, and A. Aiyyer (2007), West African storm tracks and their relationship to Atlantic tropical cyclones, *J. Clim.*, *20*, 2468–2483.

Hsieh, J. S., and K. H. Cook (2007), A study of the energetics of African easterly waves using a regional climate model, *J. Atmos. Sci.*, *64*(2), 421–440.

Kanamitsu, M., W. Ebisuzaki, J. Woollen, and Y. Shi-Keng (2002), NCEP-DOE AMIP-II Reanalysis (R-2), *Bull. Am. Meteorol. Soc.*, *83*(11), 1631–1643.

Klotzbach, P. J., A. Barnston, G. E. Bell, S. U. Camargo, J. C. Chan, A. Lea, M. A. Saunders, and F. Vitart (2012), *Seasonal Forecasting of Tropical Cyclones. Global Guide to Tropical Cyclone Forecasting*, 2nd ed., World Meteorol. Organiz., Geneva, Switzerland.

Kiladis, G. N., C. D. Thorncroft, and N. M. Hall (2006), Three-dimensional structure and dynamics of African easterly waves. Part I: Observations, *Mon. Weather Rev.*, *63*(9), 2212–2230.

Landsea, C. W. (1993), A climatology of intense (or major) Atlantic hurricanes, *Clim. Dyn.*, *121*(6), 1703–1713.

Landsea, C. W., G. D. Bell, W. M. Gray, and S. B. Goldenberg (1998), The extremely active 1995 Atlantic hurricane season: Environmental conditions and verification of seasonal forecasts, *Mon. Weather Rev.*, *126*(5), 1174–1193.

McCrary, R. R., D. A. Randall, and C. Stan (2014), Simulations of the West African Monsoon with a superparameterized climate model. Part II: African Easterly Waves, *J. Clim.*, *27*(22), 8323–8341.

Pasch, R. J., L. A. Avila, and J.-G. Jing (1998), Atlantic tropical systems of 1994 and 1995: A comparison of a quiet season to a near-record-breaking one, *Mon. Weather Rev.*, *126*(5), 1106–1123.

Price, C., N. Reicher, and Y. Yair (2015), Do West African thunderstorms predict the intensity of Atlantic hurricanes?, *Geophys. Res. Lett.*, *42*, 2457–2463, doi:10.1002/2014GL062932.

Raymond, D. J., and H. Jiang (1990), A theory for long-lived mesoscale convective systems, *J. Atmos. Sci.*, *47*(24), 3067–3077.

Roberts, A. J., J. H. Marsham, and P. Knippertz (2015), Disagreements in low-level moisture between (re) analyses over summertime West Africa, *Mon. Weather Rev.*, *143*(4), 1193–1211.

Roca, R., J. P. Lafore, C. Piriou, and J. L. Redelsperger (2005), Extratropical dry-air intrusions into the West African monsoon midtroposphere: An important factor for the convective activity over the Sahel, *J. Atmos. Sci.*, *62*(2), 390–407.

Saha, S., et al. (2006), The NCEP climate forecast system, *J. Clim.*, *19*(15), 3483–3517.

Schwendike, J., and S. C. Jones (2010), Convection in an African Easterly Wave over West Africa and the eastern Atlantic: A model case study of Helene (2006), *Q. J. R. Meteorol. Soc.*, *136*, 364–396.

Simpson, R. H., N. Frank, D. Shideler, and H. M. Johnson (1968), Atlantic tropical disturbances, *Mon. Weather Rev.*, *96*(4), 251–259.

Simpson, R. H., N. Frank, D. Shideler, and H. M. Johnson (1969), Atlantic tropical disturbances of 1968, *Mon. Weather Rev.*, *97*, 240–255.

Skinner, C. B., and N. S. Diffenbaugh (2014), Projected changes in African easterly wave intensity and track in response to greenhouse forcing, *Proc. Natl. Acad. Sci. U.S.A.*, *111*(19), 6882–6887.

Thorncroft, C., and K. Hodges (2001), African Easterly Wave variability and its relationship to Atlantic Tropical Cyclone Activity, *J. Clim.*, *14*, 1166–1179.

Tyner, B., and A. Aiyyer (2012), Evolution of African Easterly Waves in potential vorticity fields, *Mon. Weather Rev.*, *140*(11), 3634–3652.

Wheeler, M., and G. N. Kiladis (1999), Convectively coupled equatorial waves: Analysis of clouds and temperature in the wavenumber frequency domain, *J. Atmos. Sci.*, *56*, 374–399.

Wilks, D. S. (2011), *The Bootstrap in Statistical Methods in the Atmospheric Sciences*, Elsevier, pp. 172–178, San Diego, Calif.