JOURNAL OF GEOPHYSICAL RESEARCH, VOL. 116, D09114, doi:10.1029/2010JD015011, 2011

Variations in mean annual tropical cyclone size in the Atlantic

Steven Quiring,[1] Andrea Schumacher,[1] Chris Labosier,[1] and Laiyin Zhu[1]

Received 3 September 2010; revised 24 February 2011; accepted 3 March 2011; published 14 May 2011.

[1] Previous research has focused on predicting tropical cyclone (TC) size in near real time for individual storms. The purpose of this study is to develop models to explain interannual variations in mean Atlantic TC size, as measured by radius of maximum winds (RMAX) and radial extent of 34 knot winds (17 m s^{-1}; R34), and to identify the nature of the relationship between various environmental and storm-related characteristics and TC size. Our analysis demonstrates that mean annual TC size varies systematically among the subbasins in the Atlantic and therefore it is inappropriate to develop a single model for TC size for the entire Atlantic basin. The most important variable for explaining variations in mean annual TC size is the maximum tangential wind (VMAX). VMAX is negatively related to RMAX in all subbasins and positively related to R34 in all subbasins except the Gulf of Mexico, suggesting that years with more intense TCs tend to have smaller (larger) than average RMAX (R34). Other factors, such as the relationships between sea surface temperature, sea level pressure, and Niño 3.4 suggest that environmental factors may play a secondary role in modulating mean annual TC size. Although there are some similarities with the models developed for predicting short-term changes in TC size, our results indicate that it is not appropriate to apply these models to explain variations in TC size at larger spatial scales and longer temporal scales.

Citation: Quiring, S., A. Schumacher, C. Labosier, and L. Zhu (2011), Variations in mean annual tropical cyclone size in the Atlantic, *J. Geophys. Res.*, *116*, D09114, doi:10.1029/2010JD015011.

1. Introduction

[2] It is well established that the potential damage a tropical cyclone (TC) can cause is proportional to the cube of the wind speed. An index commonly used to describe the potential destructiveness of TCs, the power dissipation index, was defined by *Emanuel* [2005] as PDI $\equiv \int(0, \tau)V_{\max}^3\,dt$, where $V_{\max}$ is the maximum tangential wind speed and τ is the lifetime of the TC. Although the area influenced by the TC is accounted for in the original formulation of *Emanuel* [2005] of total power dissipation, a simplifying assumption was made to remove it from the PDI because of the difficulty in obtaining historical data on TC size. TC size influences destructive potential because it is often related to the areal extent of a storm's precipitation field, which in turn impacts the extent of inland flooding risk [*Weatherford and Gray*, 1988]. Storm surge is also a function of TC size and larger TCs are generally associated with greater surge [*Irish et al.*, 2008]. A recent study has shown that surge can vary by as much as 30% with realistic changes in TC size [*Irish et al.*, 2008]. From a socioeconomic viewpoint, for a given intensity a larger TC may require a more expansive and longer-evacuation time scale than a smaller storm [*Whitehead*, 2003]. Therefore, larger TCs tend to be more damaging and more costly.

[3] Currently, the main source of operational guidance for TC size is a scheme that relies on climatology and persistence [*Knaff et al.*, 2007]. The lack of available data on TC structure and TC size remains a significant challenge both for real-time applications and for long-term studies. Aircraft reconnaissance is the most accurate method for obtaining information on the TC wind field [*Mueller et al.*, 2006]. However, these data are typically only available for TCs that are threatening the United States. Therefore, a number of additional methods for estimating TC size and structure have been developed. *Demuth et al.* [2004, 2006] derived a statistical method for estimating TC wind radii using parameters derived from microwave remote sensing. However, the spatial and temporal resolution of the microwave data limits their utility for real-time forecasting applications. To overcome this limitation *Mueller et al.* [2006] and *Kossin et al.* [2007] developed an approach using infrared (IR) satellite data to estimate TC size. The advantage of their approach is that IR data are available continuously over the tropics [*Kossin et al.*, 2007; *Mueller et al.*, 2006]. *Kossin et al.* [2007] developed three algorithms for estimating various metrics of TC size/structure. These algorithms utilize near real time using IR satellite data and three TC characteristics (maximum wind velocity (VMAX), age of the storm and latitude) to model changes in TC size. QuikSCAT scatterometer data has also been used to investigate TC size and to develop an understanding of TC size distributions [*Chavas*

[1]Department of Geography, Texas A&M University, College Station, Texas, USA.

0148-0227/11/2010JD015011

and Emanuel, 2010]. Unfortunately, QuikSCAT ceased to operate in November 2009 and has not been replaced. All of these approaches have strengths and weaknesses and the estimates of TC size can be quite disparate. For example, *Dean et al.* [2009] demonstrated that there is significant disagreement between the estimates of *Demuth et al.* [2006] and *Kossin et al.* [2007] of TC size. This study uses the estimates of TC size that are recorded operationally and are available in the Extended Best Track (EBT) data set (1988 to 2008) [*Demuth et al.*, 2006].

[4] Researchers have identified several factors that influence TC size, which include both external forcing and internal processes [e.g., *Liu and Chan*, 2002; *Maclay et al.*, 2008; *Weatherford and Gray*, 1988]. Internal processes can lead to drastic TC size changes [*Maclay et al.*, 2008]. One such process, known as an eye wall replacement cycle, is characterized by the development of a secondary outer eye wall that contracts until it replaces the existing smaller eye wall, which results in an expansion of the surface wind field [*Willoughby et al.*, 1982]. This broadening of the surface wind field can be particularly dangerous when it occurs during landfall because of the increased coastal area that receives storm surge and wind damage. For example, *Kossin and Sitkowski* [2009] reported that Hurricane Katrina (2005) produced stronger and more damaging storm surge than expected because of the broadening of the wind field associated with the secondary eye wall. Statistical models have demonstrated success in diagnosis and short-term prediction of secondary eye wall formation in hurricanes [*Kossin and Sitkowski*, 2009], but longer-range prediction with numerical models is challenging because of the stochastic nature and small scale of internal processes. The models of TC size developed by *Kossin et al.* [2007] for predicting short-term (6 h) changes in TC size are based on VMAX, age of the storm and latitude. *Kossin et al.* [2007] found that VMAX was the most important variable and that latitude and storm age were of lesser importance. As expected, VMAX is directly correlated with the radius of 34 knot winds (R34) (e.g., stronger storms are associated with larger R34) and inversely correlated with the radius of maximum winds (RMAX) (e.g., as the strength of the storm increases, RMAX decreases). *Kossin et al.* [2007] included the age of the storm (in hours) to account for the natural broadening of the wind field over time, and latitude was included to represent variations in the Coriolis force. Both storm age and latitude were found to be positively correlated with R34 and RMAX, but these relationships were only about half as strong as the relationship with VMAX [*Kossin et al.*, 2007]. These three measures were supplemented by seven IR-derived variables which helped to reduce the error in the TC size predictions.

[5] While progress has been made in terms of developing real-time predictions of TC size and size change, little work has focused on predictability at larger spatial scales and over longer time periods. A study of northwest Pacific typhoons found interannual variability in average size could be related to annual variations in synoptic flow patterns [*Chan and Yip*, 2003]. Although this study only considered a 3 year sample, it suggests that external forcings may play a significant role in modulating annual average TC size over a given basin.

[6] This purpose of this study is to expand upon the analysis of *Chan and Yip* [2003] by examining annual variations in basin average TC size in the Atlantic, as measured by RMAX and R34. This study is motivated by the need for developing diagnostic models of TC size that are applicable at larger spatial and temporal scales than those previously developed for real-time forecasting applications [*Kossin et al.*, 2007; *Mueller et al.*, 2006]. This study was undertaken as part of a project investigating future risk from hurricane winds and surge. Future risk will be established using a series of models that consider changes in TC frequency, intensity and size for a variety of future climate scenarios and their joint impact on electrical infrastructure in the United States. Future risk will be assessed using data from general circulation models and models of annual TC frequency, intensity and size. It is unknown whether existing models that are employed for short-term predictions of TC size for a single storm are also appropriate for explaining mean annual TC size at the subbasin and basin scale. An improved understanding of interannual (and longer-term) variations in TC size has implications for examining future changes in risk from hurricane winds and surge, as well as for adaptation and coastal planning activities. This paper addresses two research questions. (1) Can diagnostic statistical models be developed to explain interannual variations in Atlantic TC size (e.g., R34 and RMAX)? (2) Which TC and environmental variables are useful for explaining interannual variations in TC size?

[7] Variations in R34 and RMAX are analyzed in relation to large-scale environmental conditions and other TC properties that have been previously found to influence TC size [e.g., *Chan and Yip*, 2003; *Weatherford and Gray*, 1988]. Section 2 identifies and defines the variables used in this analysis and provides background on the previous studies that motivated their selection. Section 3 describes the data sources, averaging techniques, and quality control procedures used. Simple linear correlations are used to examine the relationships between TC size and environmental and storm-related variables, the results of which are shown in section 4. Multiple linear regression was performed to develop diagnostic models, and the resulting models and validation results are presented in section 5. Section 6 describes some of the limitations of this study, and section 7 provides conclusions and a potential application of this work.

2. Variable Selection

2.1. Dependent Variables: Measures of TC Size

[8] TC size is measured in a variety of ways. Each metric has its own strengths and weaknesses related to availability, measurement uncertainty and utility. Measures of inner core size, such as the radius of maximum winds (RMAX) and eye diameter, can be measured directly by aircraft reconnaissance or remotely by radar and satellite. Both methods provide information about storm structure and the location of strongest winds. Yet these values do not necessarily provide a complete picture of the destructive potential of a TC, since storms of different intensities can have similar inner core sizes. For example, Hurricane Katrina on 25 August 2005 at 18z had an RMAX of 15 nautical miles (1 nautical mile =

Table 1. Variables Considered for Their Potential Influence on Tropical Cyclone (TC) Size

Abbreviation	Description
VMAX	maximum surface tangential velocity (kt)
TCLAT	TC latitude (°N)
TCSPD	TC forward speed (kt)
SST	sea surface temperature (°C)
MSLP	mean sea level pressure (mbar)
RHUM	600 mbar relative humidity (%)
VOR	850 mbar vertical vorticity ($\times 10^{-5}$ s^{-1})
VSHR	850–200 mbar vertical shear (kt)
N34	Niño 3.4 SST anomaly (°C)

1.852 km) and a VMAX of 60 knots, while Hurricane Ike on 5 September 2008 at 0z also had an RMAX of 15 nautical miles and a VMAX of 115 knots.

[9] Often times, measures of the radial extent of a specific wind speed are used to classify TC size. Metrics of this type include R34, R50, and R64, which measure the radial extent of 34 knots (17 m s^{-1}, tropical storm force), 50 knots (26 m s^{-1}) and 64 knots (33 m s^{-1}, hurricane force) winds, respectively. These metrics are directly applicable to storm surge estimates [*Irish et al.*, 2008] and the issuance of tropical storm and hurricane watches and warnings by the National Hurricane Center and Tropical Cyclone Conditions of Readiness (TCCOR) by Department of Defense installations. The downside of these metrics is that they are difficult to measure in situ and have only been available via satellite remote sensing methods for a little over a decade [*Knaff and DeMaria*, 2006]. Other size metrics attempt to classify the complete size of a TC system (i.e., the radius to the boundary between the TC environment and the ambient environment) and include the radius of the outermost closed isobar (ROCI) and the outer radius (R_0) [*Dean et al.*, 2009]. *Dean et al.* [2009] define the outer radius of the storm (R_0) as the radius where fluctuations in the surface wind field can no longer be directly associated with the tropical storm.

[10] The two size parameters considered in this study are RMAX and R34. Both are measures of TC size that are recorded operationally and are available in the Extended Best Track (EBT) data set [*Demuth et al.*, 2006]. In addition, annual average values of RMAX and R34 in the Atlantic are not significantly correlated at the 95% level (r = 0.08) using a two-sided Student's t test, suggesting that they represent independent measures of TC size over the temporal (i.e., annual) and spatial (i.e., Atlantic basin) scales considered in this analysis.

2.2. Independent Variables: Environmental and Storm-Related Parameters

[11] Several environmental factors have been identified as influencing TC size as well as size change. *Emanuel* [1986] developed a steady state analytical framework to describe the maintenance of mature TCs. In this framework, it was expected that as sea surface temperature increased, the extent of the outer winds (e.g., R34) would also increase. Prior studies in the northwest Pacific basin found that larger typhoons, as measured by metrics similar to R34, tended to form within a broad, strong monsoon "gyre" [*Liu and Chan*, 2002; *Weatherford and Gray*, 1988]. Monsoon gyres are characterized by broad low pressure and cyclonic vorticity at low levels. In an observational study by *Maclay et al.* [2008], statistical testing indicated that vertical shear was one of the most significant environmental forcings associated with increases in TC inner core kinetic energy, which is a measure of both TC size and intensity. According to *Maclay et al.* [2008] the relationship between shear and TC size is dependent upon the strength of shear. Weak shear is associated with increases in TC intensity, but not TC size. Moderate shear is associated with increases in TC size and lesser increases in TC intensity. Strong shear is not associated with increases in TC intensity or TC size. Recently, idealized numerical experiments were used to show that dry environments produced simulated TCs with less precipitation outside the core, a narrow potential vorticity distribution, and a smaller radial extent of the tangential wind field [*Hill and Lackmann*, 2009]. There is typically less TC activity in the Atlantic and TCs tend to be weaker during El Niño events because of increased upper level westerly winds and an associated increase in vertical wind shear [*Emanuel et al.*, 2008; *Gray*, 1984]. *Kimball and Mulekar* [2004] demonstrated that mean TC size is also smaller during El Niño years because of the larger proportion of weaker storms. On the basis of these prior studies, the environmental variables considered for this study include sea surface temperature (SST), 850 mbar vertical vorticity (VOR), mean sea level pressure (MSLP), 850–200 mbar vertical shear (VSHR), 600 mbar relative humidity (RHUM), and Niño 3.4 SST anomalies (N34).

[12] Past work also suggests that certain storm-related characteristics may influence the size of a TC [*Kossin et al.*, 2007; *Mueller et al.*, 2006]. The modeling framework developed by *Emanuel* [1986] indicates the size of outer core winds (e.g., R34) in a TC should increase as TC intensity increases, although observational analyses have found this correlation to be weak [*Merrill*, 1984; *Weatherford and Gray*, 1988]. Conversely, observations show that a TC intensifies as its eye wall contracts and RMAX becomes smaller [*Willoughby et al.*, 1982]. Energy balance arguments also suggest that TCs with smaller RMAX should attain stronger intensities [*Shen*, 2006]. TCs have been observed to grow as they move poleward and recurve [*Merrill*, 1984; *Weatherford and Gray*, 1988], suggesting size may be a positive function of latitude. Asymmetries induced by fast forward speeds are also thought to lead to an increase in TC size [*Schwerdt et al.*, 1979]. As such, several storm-related variables were also considered for their influence on annual average TC size, including intensity (VMAX), latitude of the center of the storm (TCLAT), and forward speed (TCSPD). A list of the independent variables used in this study is given in Table 1.

3. Data

[13] TC-related variables, including TC size parameters (RMAX and R34) and TC characteristics (VMAX, TCLAT and TCSPD) were obtained from the Extended Best Track (EBT) data set. Although certain measures of TC size, including radius of maximum winds and R34, are routinely estimated by the National Hurricane Center (NHC), these data are not included in the official records of Atlantic tropical storms and hurricanes, known as HURDAT. The

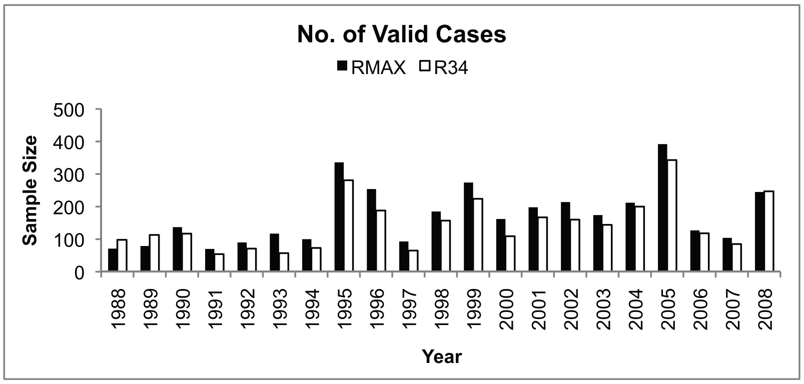

Figure 1. Number of valid cases per year for radius of maximum winds (RMAX) (white) and R34 (black).

EBT supplements HURDAT with information about TC size. Under the Risk Prediction Initiative, operational TC size data were digitized and combined with HURDAT data from 1988 to 1997. From 1998 to the present, National Environmental Satellite, Data, and Information Service's (NESDIS) Office of Oceanic and Atmospheric Research (OAR) has continued to update the EBT to aid in the development of satellite algorithms.

[14] The EBT provides a single value for VMAX, TCLAT, RMAX and TC position (from which TCSPD is computed) and TC radii (i.e., R34, R50 and R64) are provided in all four quadrants (northeast, northwest, southeast, southwest) at each 6 hourly forecast time. In this study, a mean value for R34, R50 and R64 at each forecast time was calculated by averaging the radii from all four quadrants, with the requirement that at least one radius must be reported to compute the average. Radii data were quality controlled so that physical conditions inherent in the TC radial wind profile (R64 ≤ R50 ≤ R34) were maintained. Size estimates east of 55°W were deemed less reliable because of the lack of aircraft reconnaissance data and hence were not used [*Demuth et al.*, 2006; *Knaff et al.*, 2007]. Extratropical cases, as identified in EBT, were also excluded from the analysis because when a TC goes through extratropical transition, it undergoes significant structural changes and begins to interact with its environment in different ways [*Jones et al.*, 2003]. In addition, observations over land and those that did not occur between 1 June and 30 November were also excluded from the analysis.

[15] The version of the EBT used in this study includes Atlantic TC size data from 1988 to 2008. These data include 8859 distinct forecast times. The quality control measures described above were applied to the EBT data and entries were removed that were: east of 55°W (3342), extratropical (1082), over land (937), before 1 June or after 30 November (282) and those that failed the logic test R64 < R50 < R34 (24). Some cases failed more than one of the quality control criteria. A total of 4665 cases were removed by quality control, reducing the original 8859 cases to 4194. Since the EBT size data are estimated from operational measurements, RMAX and R34 values are not necessarily available at each forecast time. After removing cases missing relevant TC size data, a total of 3634 (3071) RMAX (R34) values were retained for analysis. The number of valid cases retained per year is shown in Figure 1.

[16] The large-scale atmospheric variables used in this analysis were derived from the daily NCEP/NCAR Reanalyses [*Kalnay et al.*, 1996]. The time period of interest for this study is the Atlantic hurricane season. As such, all variables were averaged from 1 June to 30 November to obtain a single value for each hurricane season (1988–2008). For convenience, these are referred to as annual values in this paper, although they are technically hurricane season (June to November) values. MSLP and RHUM were available directly from the reanalyses, and VSHR and VOR were computed from the horizontal wind fields. Atlantic SST are from the National Oceanic and Atmospheric Administration (NOAA) Extended Reconstructed Sea Surface Temperature V3b data set and they were obtained from NOAA's Earth System Research Laboratory (http://www.esrl.noaa.gov/psd/). Niño 3.4 sea surface temperature anomaly (N34; 5°N to 5°S, 170°W to 120°W) data were also obtained from NOAA's Earth System Research Laboratory (http://www.esrl.noaa.gov/psd/).

[17] TC size has been shown to vary by subbasin within the Atlantic [*Kimball and Mulekar*, 2004]. Therefore, the Atlantic (ATL) was divided into three subbasins: Caribbean (CAR), Gulf of Mexico (GMX) and North Atlantic (NAT) (Figure 2). An areal average of VSHR, VOR, RHUM and SST were computed for the Atlantic study region and the three subbasins. Since the area covered by each NCEP/NCAR Reanalyses grid cell varies as a function of latitude, it is not appropriate to calculate an unweighted arithmetic mean based on equal weighting of all grid cells that are within the ATL and the three subbasins. An unweighted mean places too much (little) emphasis on higher (lower) latitude grid cells. Therefore, an area-weighted mean was calculated for each subbasin by weighting each grid cell by the area of the grid box divided by the average grid box area in that subbasin. Therefore, the influence of each grid cell on the mean is proportional to its area.

[18] Descriptive statistics of RMAX and R34 in each of the three subbasins and over the entire Atlantic are shown in Table 2. Mean annual RMAX and R34 are smallest in the Caribbean subbasin. The Gulf of Mexico has the largest mean annual RMAX values, although values are similar to

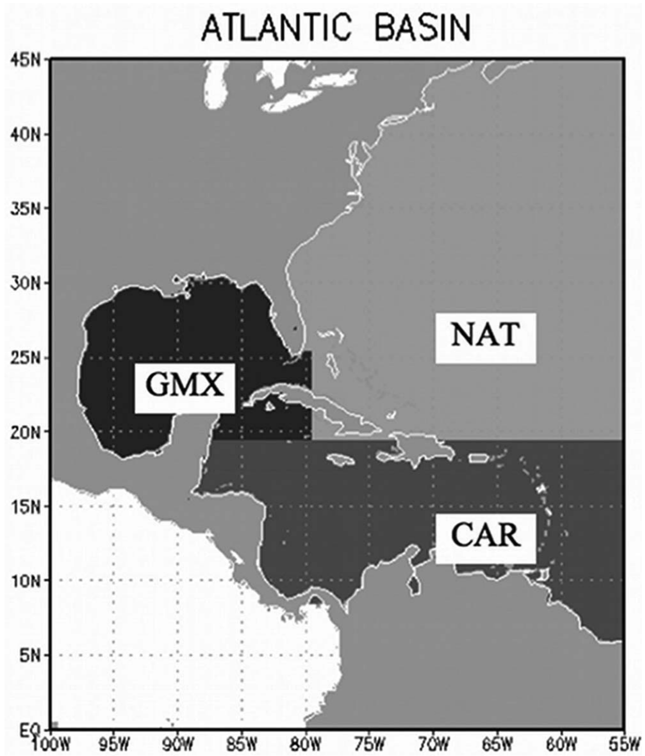

Figure 2. Spatial domain used for this study. The Atlantic basin domain is composed of three subbasins: Caribbean (CAR), North Atlantic (NAT), and Gulf of Mexico (GMX). Only Atlantic data west of 55°W are included.

those in the North Atlantic. R34 is largest in the North Atlantic, which may be due to the larger number of recurving TCs with asymmetric and expanding wind fields in that subbasin. The Gulf of Mexico has the largest variance in mean annual values of RMAX and the North Atlantic has the largest variance in mean annual values of R34. These statistical differences motivate the use of different spatial domains (i.e., entire Atlantic basin and the three subbasins) in the following analyses.

4. Correlations

[19] As a first step, linear correlations between annual average RMAX and R34 and each of the potential predictors were examined for the entire basin and each of the three subbasins (Tables 3 and 4, respectively). Correlations were considered significant if the Pearson correlation coefficient (r) was statistically significant at the 95% level using a two-sided Student's t test. Before correlations were computed, an outlier analysis was performed on the TC size parameters (RMAX and R34) to identify any values greater than 3σ from the mean. Only one outlier was identified. The annual average RMAX in the North Atlantic (NAT) for 1988 was 3.9σ larger than the sample mean. Further examination revealed that there were only three valid RMAX measurements in the EBT in 1988. This year was excluded from the correlation and regression analyses for RMAX in the North Atlantic because of the small sample size.

[20] The only predictor found to be significantly correlated with RMAX in the Atlantic and all three subbasins was VMAX. The negative sign of the correlation coefficient suggests that years with more intense (less intense) TCs tend to have smaller (larger) mean RMAX. This relationship has been shown for individual TCs [*Shen*, 2006; *Willoughby et al.*, 1982]. This result also agrees with the findings of *Kossin et al.* [2007] and it suggests that the relationship they identified for short-term prediction of TC size also holds true when annual basin-averaged TC size data are considered. In agreement with *Kossin et al.* [2007], VMAX is the most important variable for explaining variations in RMAX. There is, however, marked variation in the strength of the relationship between VMAX and RMAX across the subbasins. The strongest correlation is found in the Caribbean and the weakest correlation is in the North Atlantic.

[21] In the Caribbean subbasin, RHUM is also significantly correlated with RMAX. The positive sign of the correlation coefficient suggests that increases in Caribbean midlevel relative humidity are associated with increases in mean RMAX. This result also agrees with previous findings for individual TCs [*Hill and Lackmann*, 2009], at least in an idealized modeling framework.

[22] VMAX is also the only predictor found to be significantly correlated with R34. The correlation is significant in all domains except the Gulf of Mexico and is positive, suggesting that years with more (less) intense TCs are

Table 2. Mean Tropical Cyclone Size, Standard Deviation, and Sample Size for RMAX and R34 in the Atlantic Basin (ATL), Caribbean (CAR), Gulf of Mexico (GMX), and North Atlantic (NAT) Subbasins

	RMAX				R34			
	ATL	CAR	GMX	NAT	ATL	CAR	GMX	NAT
Mean (nautical miles)	34.8	29.6	38.3	36.2	108.4	86.6	104.5	119.8
SD (nautical miles)	21.4	18.6	26.3	20.1	50.7	37.4	46.2	54.0
N	3634	982	718	1934	3071	780	597	1694

Table 3. Correlation (r) Between RMAX and Selected Variables in the Atlantic Basin (ATL), Caribbean (CAR), Gulf of Mexico (GMX), and North Atlantic (NAT) Subbasins[a]

	VMAX	TCLAT	TCSPD	SST	MSLP	RHUM	VOR	VSHR	N34
ATL	**−0.47**	−0.18	−0.19	0.06	−0.26	−0.15	0.24	−0.06	−0.17
CAR	**−0.64***	−0.04	−0.20	−0.41	0.18	**0.45**	0.16	0.27	0.26
GMX	**−0.53**	−0.32	−0.07	0.31	−0.02	−0.36	0.05	−0.06	−0.07
NAT	**−0.45**	−0.02	−0.06	0.20	−0.22	−0.11	−0.10	−0.12	−0.21

[a]Values in bold are significant at the 95% level, and values with an asterisk are significant at the 99% level using a two-tailed Student's t test.

Table 4. Correlation (r) Between R34 and Selected Variables in the Atlantic Basin (ATL), Caribbean (CAR), Gulf of Mexico (GMX), and North Atlantic (NAT) Subbasins[a]

	VMAX	TCLAT	TCSPD	SST	MSLP	RHUM	VOR	VSHR	N34
ATL	**0.55***	0.04	−0.04	0.28	−0.29	−0.01	0.31	−0.06	−0.34
CAR	**0.81***	0.03	−0.30	0.30	−0.39	−0.05	0.02	−0.10	−0.29
GMX	0.39	−0.19	0.08	0.22	−0.32	0.22	0.40	−0.14	−0.28
NAT	**0.62***	−0.16	0.10	0.27	−0.05	−0.14	0.01	−0.17	−0.33

[a]Values in bold are significant at the 95% level, and values with an asterisk are significant at the 99% level using a two-tailed Student's t test.

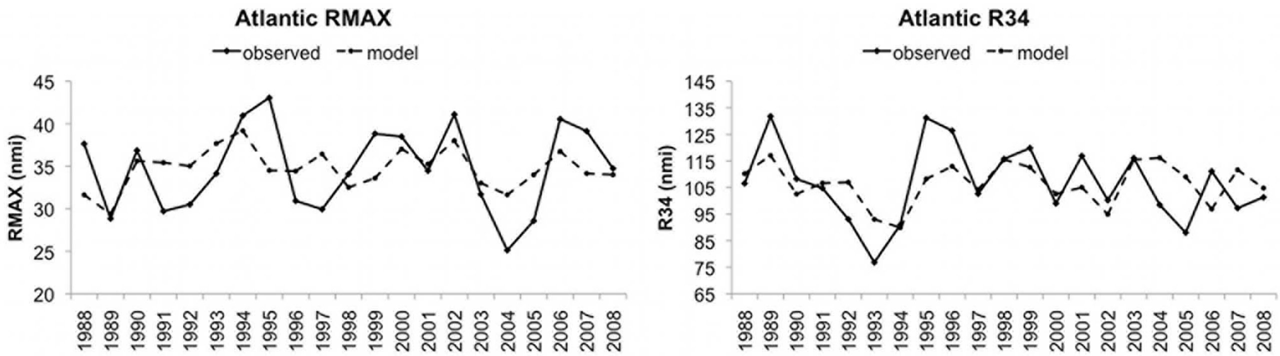

Figure 3. Time series of observed and modeled mean annual (left) RMAX and (right) R34 for the entire Atlantic basin from 1988 to 2008. Units are nautical miles.

associated with larger (smaller) mean R34. Although the structure of the wind field tends to differ from storm to storm, the shape of the wind field is generally such that wind speed decays outside of RMAX. Hence, as TC intensity increases, the radial extent of the 34 knot wind field (R34) is generally expected to expand, providing a physical rationale for this statistical correlation. The sign and strength of the correlation between VMAX and R34 are in agreement with the findings of *Kossin et al.* [2007]. As with RMAX, there is substantial variation in the strength of the relationship between VMAX and R34 across the subbasins. The strongest correlation is in the Caribbean and the weakest correlation is in the Gulf of Mexico.

[23] Although correlations with the other variables are not statistically significant (at the 95% level), they still provide some insights. There is a moderate positive correlation between SST and R34 in the ATL and all subbasins. This correlation suggests that years with elevated SSTs are associated with increases in TC size. This finding is in agreement with the theoretical modeling work of *Emanuel* [1986]. There also is a consistent negative correlation between N34 and R34. This correlation suggests that years associated with lower than normal SSTs in the eastern equatorial Pacific are associated with large TC sizes in the Atlantic and all subbasins. As demonstrated by *Kimball and Mulekar* [2004] TC size is also larger (smaller) during La Niña (El Niño) years. This may be due to the larger proportion of stronger (weaker) storms. Finally, there is a consistent negative correlation between MSLP and R34 in the ATL and all subbasins. This indicates that years with lower than normal MSLP are generally associated with larger storms. Similar to N34 we expect that this may be due to the larger proportion of stronger (weaker) storms during years with lower (higher) MSLP [*Knaff*, 1997].

[24] It is also notable which variables are not strongly correlated with R34. In contrast to the findings of *Kossin et al.* [2007], latitude was not a significant predictor of TC size. The sign of the correlations between R34 and latitude were variable and the strength of the correlations was weak across the three subbasins. There was also not a strong or coherent relationship between the forward speed of the storm and mean annual variations in R34. These findings illustrate that it is inappropriate to apply models that were developed to forecast short-term changes in TC size to explain/predict TC size at larger spatial scales and longer temporal scales.

5. Model Development

[25] Multiple linear regression (MLR) was used to develop diagnostic models of RMAX and R34 over the Atlantic and each of the three subbasins. Collinearity between predictors can make it difficult to estimate the contributions of individual predictors [*Neter et al.*, 1989]. Hence, prior to performing MLR, multicollinearities were reduced by identifying all pairs of variables whose correlation coefficient values were significant at the 95% level using a two-sided Student's t test and eliminating the variable that was least correlated with TC size (Tables 3 and 4).

[26] A forward stepping procedure was used to determine the final models. For this procedure, all independent variables (after reduction of collinearities) are entered into the regression model. For each step, the independent variable with the largest p value is removed and the model is recalculated. The forward stepping ceases once every independent variable has a p value of less than or equal to 0.05. Since only 21 years of TC size data are available in the EBT data set, there is a potential for overfitting the data, especially if too many predictors are included in our models [*DelSole and Shukla*, 2009]. The methodology outlined here resulted in models that were a function of no more than two predictors, which suggests overfitting has been minimized.

Table 5. Sample Characteristics and Statistical Measures of Model Fit for Observed, Modeled, and Cross-Validated Mean Annual Atlantic (ATL) RMAX From 1988 to 2008[a]

	Observed	Model	Cross-Validated
Mean (nautical miles)	34.7	34.7	34.7
SD (nautical miles)	5.0	2.4	2.3
Min (nautical miles)	25.1	29.4	29.6
Max (nautical miles)	43.1	39.2	38.7
MAE (nautical miles)		3.7 (10.5%)	4.0 (11.5%)
R^2		0.22	0.10
d		0.60	0.51

[a]Statistical measures of model fit include mean absolute error (MAE), coefficient of determination (R^2), and index of agreement (d [*Willmott*, 1981]).

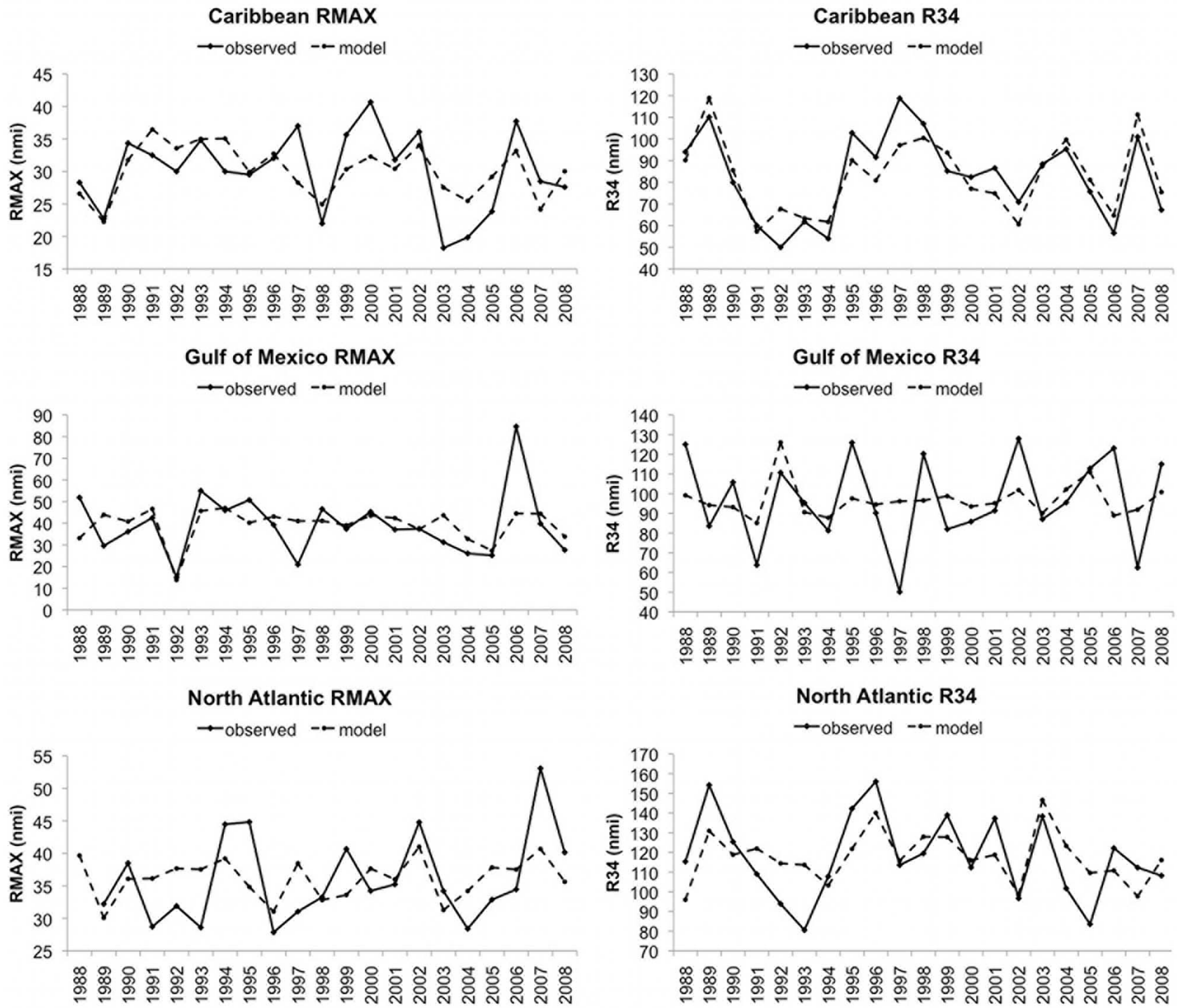

Figure 4. Time series of observed and modeled mean annual (left) RMAX and (right) R34 for the (top) Caribbean, (middle) Gulf of Mexico, and (bottom) north Atlantic subbasins. Units are nautical miles.

[27] Models are evaluated based on their physical interpretation. Goodness of fit is assessed using mean absolute error (MAE), coefficient of determination (R^2), and index of agreement (d [*Willmott*, 1981]). Since the EBT data set only includes 21 years of TC size data, a leave-one-out cross-validation procedure, similar to the approach used by *Gray et al.* [1992], was employed to estimate the diagnostic skill of the developed models.

5.1. RMAX Models

[28] MLR yields a model for RMAX that is a function of VMAX. The resulting model equation for RMAX over the entire Atlantic basin is $\mathrm{RMAX_{ATL}} = 49.67 - 0.24*\mathrm{VMAX}$. The coefficient for VMAX is negative, indicating that a year with more intense TCs should have a smaller mean RMAX. As discussed in section 2, this result is consistent with observations [*Willoughby et al.*, 1982] and theoretical calculations [*Shen*, 2006] for individual TCs. In addition, this model compares favorably with the RMAX model developed by *Kossin et al.* [2007]. Model-derived versus observed annual mean RMAX is shown in Figure 3 (left). Statistical measures for goodness of fit for the Atlantic RMAX model are shown in Table 5. The coefficient of determination for the developmental (cross validated) sample is R^2 = 0.22 (0.10), the mean absolute error is 3.7 nautical miles (4.0 nautical miles) or 10.5% (11.5%), and the index of agreement is d = 0.60 (0.51). While the coefficient of determination is relatively small, it compares favorably with the RMAX model (R^2 = 0.20) of *Kossin et al.* [2007]. The decrease in R^2 and d in the cross validation suggests that the model is overfitting the developmental data, a problem that is common when regression is used on small samples. The goodness of fit for the cross-validated data are likely more representative of the true skill of the model.

[29] The previous correlation analysis results in Table 2 show that the relationships between TC size and the candidate predictors differed significantly by subbasin. Hence,

Table 6. Sample Characteristics and Statistical Measures of Model Fit for Observed and Modeled Mean Annual Caribbean (CAR), Gulf of Mexico (GMX), and North Atlantic (NAT) RMAX from 1988 to 2008[a]

	CAR		GMX		NAT	
	Observed	Model	Observed	Model	Observed	Model
Mean (nautical miles)	30.2	30.2	39.3	39.3	36.0	36.0
SD (nautical miles)	6.1	3.9	14.7	7.8	6.8	3.1
Min (nautical miles)	18.2	22.3	15.0	13.9	27.9	30.1
Max (nautical miles)	40.7	36.5	84.6	47.1	53.1	41.0
MAE (nautical miles)		3.8 (12.5%)		8.3 (21.1%)		5.1 (14.1%)
R^2		0.41		0.28		0.20
D		0.74		0.64		0.58

[a]Statistical measures of model fit include mean absolute error (MAE), coefficient of determination (R^2), and index of agreement (d [*Willmott*, 1981]).

separate models were developed for each of the three subbasins shown in Figure 2. The resulting model equations for the Caribbean (CAR), Gulf of Mexico (GMX) and North Atlantic (NAT) subbasins are $\mathrm{RMAX_{CAR}} = 42.75 - 0.21*\mathrm{VMAX}$, $\mathrm{RMAX_{GMX}} = 62.40 - 0.41*\mathrm{VMAX}$, and $\mathrm{RMAX_{NAT}} = 52.27 - 0.26*\mathrm{VMAX}$, respectively. Model-derived versus observed annual average RMAX in the three subbasins is shown in Figure 4 (left). Comparison of the subbasin models shows a robust negative relationship between annual average RMAX and VMAX that was also present in the model for the entire basin. The goodness of fit (Table 6), as measured by R^2 and d, of the subbasin models are somewhat better than for the whole basin model.

5.2. R34 Models

[30] The model developed for the North Atlantic for R34 is also solely dependent on VMAX. The resulting model equation for R34 over the entire Atlantic basin is $\mathrm{R34_{ATL}} = 47.19 + 0.89*\mathrm{VMAX}$. The positive coefficient suggests that seasons with more intense TCs should have a larger mean R34. This relationship is likely related to R34 being defined as the radial extent of a fixed wind speed. As a TC intensifies, generally both inner and outer core winds will intensify which will lead to an outward expansion of the 34 knot winds. Hence, it is not surprising that a year with more intense Atlantic TCs will also have a larger mean R34. A similar result has also been found for individual TCs, although their results were based on TCs in the western Pacific [*Weatherford and Gray*, 1988]. Model-derived versus observed annual average R34 is shown in Figure 3 (right). Statistical measures for goodness of fit for the Atlantic R34 model are shown in Table 7 and are similar to those for the Atlantic RMAX model. The coefficient of determination for the developmental (cross-validated) sample is $R^2 = 0.30$ (0.17), the mean absolute error is 9.3 nautical miles (10.2 nautical miles) or 8.7% (9.6%), and the index of agreement is $d = 0.67$ (0.59). Once again, the cross-validated fit statistics suggest the model will have a lower level of diagnostic skill on an independent data set.

[31] The resulting model equations for the Caribbean (CAR), Gulf of Mexico (GMX) and North Atlantic (NAT) subbasins are $\mathrm{R34_{CAR}} = 40.06 + 0.97*\mathrm{VMAX} + 1.93*\mathrm{RHUM}$, $\mathrm{R34_{GMX}} = 65.42 + 0.51*\mathrm{VMAX}$, and $\mathrm{R34_{NAT}} = 48.45 + 1.06*\mathrm{VMAX}$, respectively. Model-derived versus observed annual average R34 in the three subbasins is shown in Figure 4 (right). Comparison of the subbasin models shows a robust positive relationship between annual average R34 and VMAX. The Caribbean model is also a positive function of RHUM, suggesting midlevel humidity may be related to TC size (as measured by R34) in that region [*Hill and Lackmann*, 2009]. The goodness of fit of the derived models was found to vary between subbasins (Table 8), with the model for the Caribbean having much larger R^2 and d values ($R^2 = 0.75$ and $d = 0.92$) and smaller error values (MAE = 9.9%) than the Gulf of Mexico ($R^2 = 0.15$, $d = 0.46$ and MAE = 16.9%) and North Atlantic ($R^2 = 0.38$, $d = 0.72$ and MAE = 11.8%) models.

[32] It is hypothesized that the MLR approach used here appears to work best in the Caribbean subbasin because TCs in that region are more “well behaved.” In the Caribbean, TCs have fewer interactions with land, midlatitude fronts and easterlies, and oceanic inhomogeneities (e.g., the Loop Current in the Gulf of Mexico) that are not represented in our models. Hence, we might expect the models to work best in the Caribbean. This is purely conjecture, however, and further work is needed to further understand the atmospheric and oceanic processes related to TC size variations on large spatial and temporal scales so that potential predictability can be accurately assessed.

6. Limitations

[33] Our analysis has demonstrated that it is possible to develop statistically significant models of mean annual TC size for the Atlantic and its subbasins. However, there are some important caveats that should be kept in mind when attempting to interpret or apply these results. The small sample size (i.e., 21 years) is a major limitation in attempting to fit robust statistical models. The small sample size leads to instability in the multiple regression models, as demonstrated by the decrease in accuracy of the cross-validation models. It would likely require about 20 more years of data to adequately address this problem. There are also potential issues with the quality of the TC size data. As noted above, TCs east of 55°W were deemed less reliable because of the lack of aircraft reconnaissance data and hence were not used. Generally, the EBT estimates of TC size (e.g., R34 and RMAX) will be more reliable for TCs that are closer to land and those for which aircraft reconnaissance data are available. Although there are other TC size data sets, such as those developed using microwave [*Demuth et al.*, 2006], infrared [*Kossin et al.*, 2007; *Mueller et al.*, 2006] and scatterometer [*Chavas and Emanuel*, 2010] satellite data, all

Table 7. Sample Characteristics and Statistical Measures of Model Fit for Observed, Modeled, and Cross-Validated Mean Annual Atlantic (ATL) R34 From 1988 to 2008[a]

	Observed	Model	Cross-Validated
Mean (nautical miles)	106.5	106.5	106.5
SD (nautical miles)	14.3	7.8	7.8
Min (nautical miles)	76.8	89.9	89.5
Max (nautical miles)	131.8	117.1	118.7
MAE (nautical miles)		9.3 (8.7%)	10.2 (9.6%)
R^2		0.30	0.17
d		0.67	0.59

[a]Statistical measures of model fit include mean absolute error (MAE), coefficient of determination (R^2), and index of agreement (*d* [*Willmott*, 1981]).

of these approaches have their own strengths and weaknesses. *Dean et al.* [2009] demonstrated that there is significant disagreement between the estimates of TC size by *Demuth et al.* [2006] and *Kossin et al.* [2007]. Therefore, the results of this analysis may be partially dependent on our usage of the EBT to provide estimates of TC size.

[34] There is also evidence that the results of this analysis are somewhat dependent on the quality control procedures. To maximize the available data, this study used all cases from the EBT that had at least one valid R34 radius (i.e., at least one of the four quadrants). However, when a more restrictive requirement of two, three or four quadrants is employed, this has an impact on the strength of the correlations (results not shown). A preliminary sensitivity analysis demonstrated that the correlations are relatively stable (compared to the method we used) until only cases with valid wind in all four quadrants are considered. This is not surprising since there are only 2492 cases that have a valid R34 in all four quadrants. We also performed a sensitivity analysis to examine whether the results of our analysis changed if we only included cases from the most active part of the hurricane season (August to October). Although the results are generally similar (the sign and strength of the relationships generally remains the same), some additional variables become statistically significant in the R34 models. Most notably, MSLP is statistically significant in the model for the entire Atlantic as well as in the NAT subbasin. In both cases the relationship is negative which suggests that decreases in MSLP are associated with increases in R34.

[35] This paper utilizes multiple linear regression models to examine the interannual variations in TC size in the Atlantic. Therefore, the physical inferences that can be drawn from these models are limited. Although the main findings of this paper agree with previous research in terms of the expected physical relationship to TC size, they still should be interpreted with caution. The sign and strength of the correlations provide insight and help to explain interannual variations in TC size, but do not provide direct physical insight. The spatial averaging (over the Atlantic basin or subbasins) and temporal averaging (over the hurricane season) may also complicate the interpretation and application of the results.

7. Summary, Conclusions, and Future Work

[36] Twenty-one years of Extended Best Track TC size data were used to develop models to explain interannual variations in mean Atlantic TC size (i.e., R34 and RMAX) and to identify the nature of the relationship between various environmental and storm-related characteristics and TC size. Our analysis demonstrated that mean annual TC size varies systematically among the subbasins in the Atlantic. Mean annual RMAX is largest in the Gulf of Mexico and smallest in the Caribbean. Mean annual R34 is greatest in the North Atlantic and smallest in the Gulf of Mexico. These variations suggest that it is inappropriate to develop a single model for TC size for the entire Atlantic basin.

[37] The most important variable for explaining variations in mean annual TC size is VMAX. The correlation was negative (positive) between VMAX and RMAX (R34), suggesting that years with more intense TCs tend to have smaller (larger) than average RMAX (R34). The correlation between RMAX and VMAX was significant at the 99% level in the Caribbean, and the correlation between R34 and VMAX was significant at the 99% level in all spatial domains tested except the Gulf of Mexico. Although correlations with the other environmental and storm-related variables were not strong, R34 had a positive correlation with SST in the ATL and in all subbasins, and a negative correlation with N34 and MSLP. This suggests that TC size is larger during years with warmer than normal SSTs in the Atlantic, La Niña conditions, and lower than normal MSLP. It is also notable that in contrast to previous work [e.g., *Kossin et al.*, 2007], latitude was not a significant predictor of TC size. This is probably partly because *Kossin et al.* [2007] focused on modeling TC size for an individual storm, rather than over a season.

[38] Diagnostic models of mean annual RMAX and R34 were developed using multiple linear regression. All of the models for RMAX (R34) were inversely (directly) related to

Table 8. Sample Characteristics and Statistical Measures of Model Fit for Observed and Modeled Mean Annual Caribbean (CAR), Gulf of Mexico (GMX), and North Atlantic (NAT) R34 From 1988 to 2008[a]

	CAR		GMX		NAT	
	Observed	Model	Observed	Model	Observed	Model
Mean (nautical miles)	82.8	82.8	96.9	96.9	117.6	117.6
SD (nautical miles)	19.7	17.1	22.5	8.8	21.1	13.0
Min (nautical miles)	50.0	57.3	50.1	85.1	80.5	96.0
Max (nautical miles)	118.8	118.9	128.0	126.1	156.0	146.6
MAE (nautical miles)		8.2 (9.9%)		16.4 (16.9%)		13.9 (11.8%)
R^2		0.75		0.15		0.38
d		0.92		0.46		0.72

[a]Statistical measures of model fit include mean absolute error (MAE), coefficient of determination (R^2), and index of agreement (*d* [*Willmott*, 1981]).

VMAX. All of the regression models ended up being solely functions of VMAX, with the exception of the R34 model in the Caribbean which was also a function of RHUM. The models developed in this study demonstrate that it is possible to develop skillful (relative errors were 10 to 20%) diagnostic models of mean annual TC size, particularly for R34. Although there are some similarities with the models developed for predicting short-term changes in TC size, our results indicate that it is not appropriate to apply these models to explain variations in TC size at larger spatial scales and longer temporal scales.

[39] This study is particularly important in the context of studying TC damage potential in changing climates. Size is an important factor in determining the destructive potential of TCs, and hence in order to estimate future damage potential it is necessary to parameterize TC size. The model developed for R34 suggests that if the average intensity of TCs were to increase (decrease) in future climate, we would expect average size, as measured by R34, to also increase (decrease). *Dean et al.* [2009] suggested that TC size, as represented by the outer radius (R_0), is lognormally distributed and hence can be parameterized by random sampling from a climatological distribution. Assuming the shape of the distribution of R34 does not change significantly at the same time, impact studies can randomly sample from a modified distribution to parameterize R34. This potential application will be further examined and tested in future work.

[40] **Acknowledgments.** This work was partially supported by DOE grant DE-FG02-08ER64644. The authors would like to thank Mlenge Mgendi for his contributions to a graduate class project that was the basis for this work. The authors are also grateful to the three anonymous reviewers who provided constructive comments that improved this paper.

References

Chan, J. C. L., and C. K. M. Yip (2003), Interannual variations of tropical cyclone size over the North Pacific, *Geophys. Res. Lett.*, *30*(24), 2267, doi:10.1029/2003GL018522.

Chavas, D. R., and K. A. Emanuel (2010), A QuikSCAT climatology of tropical cyclone size, *Geophys. Res. Lett.*, *37*, L18816, doi:10.1029/2010GL044558.

Dean, L., K. A. Emanuel, and D. R. Chavas (2009), On the size of Atlantic tropical cyclones, *Geophys. Res. Lett.*, *36*, L14803, doi:10.1029/2009GL039051.

DelSole, T., and J. Shukla (2009), Artificial skill due to predictor screening, *J. Clim.*, *22*, 331–345, doi:10.1175/2008JCLI2414.1.

Demuth, J. L., M. DeMaria, J. A. Knaff, and T. H. Vonder Haar (2004), Evaluation of Advanced Microwave Sounder Unit tropical cyclone intensity and size estimation algorithms, *J. Appl. Meteorol.*, *43*, 282–296, doi:10.1175/1520-0450(2004)043<0282:EOAMSU>2.0.CO;2.

Demuth, J. L., M. DeMaria, and J. A. Knaff (2006), Improvement of advanced microwave sounding unit tropical cyclone intensity and size estimation algorithms, *J. Appl. Meteorol. Climatol.*, *45*, 1573–1581, doi:10.1175/JAM2429.1.

Emanuel, K. A. (1986), An air-sea interactions theory for tropical cyclones. Part I: Steady-state maintenance, *J. Atmos. Sci.*, *43*, 585–605, doi:10.1175/1520-0469(1986)043<0585:AASITF>2.0.CO;2.

Emanuel, K. A. (2005), Increasing destructiveness of tropical cyclones over the past 30 years, *Nature*, *436*, 686–688, doi:10.1038/nature03906.

Emanuel, K. A., R. Sundararajan, and J. Williams (2008), Hurricanes and global warming: Results from downscaling IPCC AR4 simulations, *Bull. Am. Meteorol. Soc.*, *89*, 347–367, doi:10.1175/BAMS-89-3-347.

Gray, W. M. (1984), Atlantic seasonal hurricane frequency. Part I: El Niño and 30 mb quasi-biennial oscillation influences, *Mon. Weather Rev.*, *112*, 1649–1668, doi:10.1175/1520-0493(1984)112<1649:ASHFPI>2.0.CO;2.

Gray, W. M., C. W. Landsea, P. W. Mielke, and K. J. Berry (1992), Predicting Atlantic seasonal hurricane activity 6–11 months in advance, *Weather Forecast.*, *7*, 440–455, doi:10.1175/1520-0434(1992)007<0440:PASHAM>2.0.CO;2.

Hill, K. A., and G. M. Lackmann (2009), Influence of environmental humidity on tropical cyclone size, *Mon. Weather Rev.*, *137*, 3294–3315, doi:10.1175/2009MWR2679.1.

Irish, J. L., D. T. Resio, and J. J. Ratcliff (2008), The influence of storm size on hurricane surge, *J. Phys. Oceanogr.*, *38*, 2003–2013, doi:10.1175/2008JPO3727.1.

Jones, S. C., et al. (2003), The extratropical transition of tropical cyclones: Forecast challenges, current understanding, and future directions, *Weather Forecast.*, *18*, 1052–1092, doi:10.1175/1520-0434(2003)018<1052:TETOTC>2.0.CO;2.

Kalnay, E., et al. (1996), The NCEP/NCAR 40-year reanalysis project, *Bull. Am. Meteorol. Soc.*, *77*, 437–471, doi:10.1175/1520-0477(1996)077<0437:TNYRP>2.0.CO;2.

Kimball, S. K., and M. S. Mulekar (2004), A 15-year climatology of North Atlantic tropical cyclones. Part I: Size parameters, *J. Clim.*, *17*, 3555–3575, doi:10.1175/1520-0442(2004)017<3555:AYCONA>2.0.CO;2.

Knaff, J. A. (1997), Implications of summertime sea level pressure anomalies in the tropical Atlantic region, *J. Clim.*, *10*, 789–804, doi:10.1175/1520-0442(1997)010<0789:IOSSLP>2.0.CO;2.

Knaff, J. A., and M. DeMaria (2006), A multi-platform satellite tropical cyclone wind analysis system, paper presented at 14th Conference on Satellite Meteorology and Oceanography, Am. Meteorol. Soc., New Orleans, La., 28 Jan. to 2 Feb.

Knaff, J. A., C. R. Sampson, M. DeMaria, T. P. Marchok, J. M. Gross, and C. J. McAdie (2007), Statistical tropical cyclone wind radii prediction using climatology and persistence, *Weather Forecast.*, *22*, 781–791, doi:10.1175/WAF1026.1.

Kossin, J. P., and M. Sitkowski (2009), An objective model for identifying secondary eye wall formation in hurricanes, *Mon. Weather Rev.*, *137*, 876–892, doi:10.1175/2008MWR2701.1.

Kossin, J. P., J. A. Knaff, H. I. Berger, D. C. Herndon, T. A. Cram, C. S. Velden, R. J. Murnane, and J. D. Hawkins (2007), Estimating hurricane wind structure in the absence of aircraft reconnaissance, *Weather Forecast.*, *22*, 89–101, doi:10.1175/WAF985.1.

Liu, C., and J. C. L. Chan (2002), Synoptic patterns associated with small and large tropical cyclones over the western North Pacific, *Mon. Weather Rev.*, *130*, 2134–2142, doi:10.1175/1520-0493(2002)130<2134:SFPAWS>2.0.CO;2.

Maclay, K. S., M. DeMaria, and T. H. Vonder Haar (2008), Tropical cyclone inner-core kinetic energy evolution, *Mon. Weather Rev.*, *136*, 4882–4898, doi:10.1175/2008MWR2268.1.

Merrill, R. T. (1984), A comparison of large and small tropical cyclones, *Mon. Weather Rev.*, *112*, 1408–1418, doi:10.1175/1520-0493(1984)112<1408:ACOLAS>2.0.CO;2.

Mueller, K. J., M. DeMaria, J. Knaff, J. P. Kossin, and T. H. Vonder Haar (2006), Objective estimation of tropical cyclone wind structure from infrared satellite data, *Weather Forecast.*, *21*, 990–1005, doi:10.1175/WAF955.1.

Neter, J., W. Wasserman, and M. H. Kutner (1989), *Applied Linear Regression Models*, McGraw-Hill, Homewood, Ill.

Schwerdt, R. W., F. P. Ho, R. R. Watkins (1979), Meteorological criteria for standard project hurricane and probable maximum hurricane wind fields, Gulf and east coasts of the United States, *NOAA Tech. Rep. NWS 23*, Natl. Weather Serv., NOAA, Washington, D. C.

Shen, W. X. (2006), Does the size of hurricane eye matter with its intensity?, *Geophys. Res. Lett.*, *33*, L18813, doi:10.1029/2006GL027313.

Weatherford, C., and W. M. Gray (1988), Typhoon structure as revealed by aircraft reconnaissance. Part II: Structural variability, *Mon. Weather Rev.*, *116*, 1044–1056, doi:10.1175/1520-0493(1988)116<1044:TSARBA>2.0.CO;2.

Whitehead, J. C. (2003), One million dollars per mile? The opportunity costs of hurricane evacuation, *Ocean Coastal Manage.*, *46*, 1069–1083, doi:10.1016/j.ocecoaman.2003.11.001.

Willmott, C. J. (1981), On the validation of models, *Phys. Geogr.*, *2*, 184–194.

Willoughby, H. E., J. A. Clos, and M. G. Shoreibah (1982), Concentric eye walls, secondary wind maxima, and the evolution of the hurricane vortex, *J. Atmos. Sci.*, *39*, 395–411, doi:10.1175/1520-0469(1982)039<0395:CEWSWM>2.0.CO;2.

C. Labosier, S. Quiring, A. Schumacher, and L. Zhu, Department of Geography, Texas A&M University, MS 3147, College Station, TX 77843-3147, USA. (squiring@tamu.edu)