Extended-range seasonal hurricane forecasts for the North Atlantic with a hybrid dynamical-statistical model

Hye-Mi Kim[1] and Peter J. Webster[1]

Received 21 July 2010; revised 15 September 2010; accepted 20 September 2010; published 9 November 2010.

[1] A hybrid forecast model for seasonal hurricane activity in the North Atlantic is developed using a combined numerical coupled ocean-atmosphere climate and empirical prediction models. Based on a 29-yr (1981-2009) dataset, an empirical relationship developed between the number of seasonal hurricane and the large-scale variables from ECMWF hindcasts. The increase of seasonal hurricane activity correlates negatively with the sea surface temperature (SST) anomaly over the tropical East Pacific, positively with the SST anomaly over the Main Development Region (MDR) and North Atlantic and the decrease of wind shear over the MDR. The North Atlantic SST and the MDR vertical wind shear are selected as predictors based on sensitivity tests. Forecasts of these predictors are made with the ECMWF climate model run in ensemble mode thus providing a probability distribution of hurricane number. The forecast skill of the hybrid model is better than or at least competitive with publicly-available forecast models but made with a one month earlier lead-time. The hybrid model initialized in June and July 2010 forecasts an active season with 9 hurricanes. **Citation:** Kim, H.-M., and P. J. Webster (2010), Extended-range seasonal hurricane forecasts for the North Atlantic with a hybrid dynamical-statistical model, *Geophys. Res. Lett.*, *37*, L21705, doi:10.1029/2010GL044792.

1. Introduction

[2] With an increase in North Atlantic (NATL) hurricane activity in the recent decades [*Emanuel*, 2005; *Landsea*, 2005; *Webster et al.*, 2005; *Holland and Webster*, 2007] and an increase in the population of coastal areas [*Pielke and Landsea*, 1998], there has been a growing demand for extended forecasts of hurricane activity with lead times of months. Although a large proportion of hurricane activity is related directly to local thermodynamic conditions [*Goldenberg et al.*, 2001; *Saunders and Lea*, 2008], a sizeable portion is controlled indirectly by the large-scale atmosphere-ocean dynamics (such as El Niño Southern Oscillation: ENSO, the Atlantic Multidecadal Oscillation: AMO, the Atlantic Meridional Mode: AMM, and the North Atlantic Oscillation: NAO) affecting changes in large-scale circulations on decadal and interannual timescales [*Gray*, 1984; *Goldenberg et al.*, 2001; *Elsner*, 2003; *Bell and Chelliah*, 2006; *Kossin and Vimont*, 2007; *Kim et al.*, 2009; *Kossin et al.*, 2010]. Noting these associations, most hurricane forecasts are based on pre-existing empirical relationships between the hurricane activity, sea surface temperature (SST) distributions and the large-scale dynamics. For example, the Colorado State University (CSU) forecasts of hurricane activity issued in early August for upcoming season, uses information on the phase of the ENSO, the SST over the east Atlantic, sea level pressure (SLP) variability over the tropical Atlantic and the statistics of storms that have occurred earlier in the season prior to the forecast issuing date [*Klotzbach*, 2007]. For this class of models, empirical relationships between predictands and predictors are based on lag relationships from previous seasons. A second method of seasonal hurricane prediction uses dynamical information from coupled ocean-atmosphere climate models directly [*Vitart et al.*, 2007].

[3] We test the hypothesis that a combination of the two methodologies provides additional skill beyond that of the component models [*Wang et al.*, 2009]. *Wang et al.* [2009] made a first attempt using the hindcasts from the National Centers for Environmental Prediction (NCEP) Climate Forecast System (CFS) for a 26-yr (1981-2006) period to build an empirical relationship between the seasonal hurricane numbers and CFS hindcasts for SSTs and vertical wind shear in the tropical Pacific and Main Development Region (MDR). Their most skillful forecast uses only wind shear as its predictor and provides competitive skill with current empirical forecast models. Here we also test a hybrid system combining the ECMWF System 3 coupled ocean-atmosphere climate model [*Anderson et al.*, 2007] and an empirical linear regression model.

2. Data and Analysis

[4] The hurricane data used in this study are for Saffir-Simpson category storms 1 or greater obtained from the NOAA Hurricane Best Track Database [*Landsea et al.*, 2004] (http://www.aoml.noaa.gov/hrd/tcfaq/E11.html). Hurricane activity is measured by the actual number of hurricanes over the Atlantic hurricane season from 1981 to 2009. Therefore, the predictand for the hybrid system is the total number of hurricanes over the entire Atlantic hurricane season. As the active hurricane season generally begins in July, the analysis of the large-scale variables focuses on the seasonal mean compiled from July through October. The sea surface temperature (SST) data are from the Extended Reconstructed Sea Surface Temperature Version 2 (ERSSTv2) [*Smith and Reynolds*, 2004] and the zonal wind data is from ERA 40 [*Uppala et al.*, 2005] from 1981 to 1988 and from the ERA interim from 1989 to 2009 [*Berrisford et al.*, 2009]. The wind shear is defined as the magnitude of zonal wind difference between 850 and 200 hPa.

[5] The ECMWF hindcasts are used to provide predictors for the hybrid forecast model. Initial conditions for the

[1]School of Earth and Atmospheric Science, Georgia Institute of Technology, Atlanta, Georgia, USA.

0094-8276/10/2010GL044792

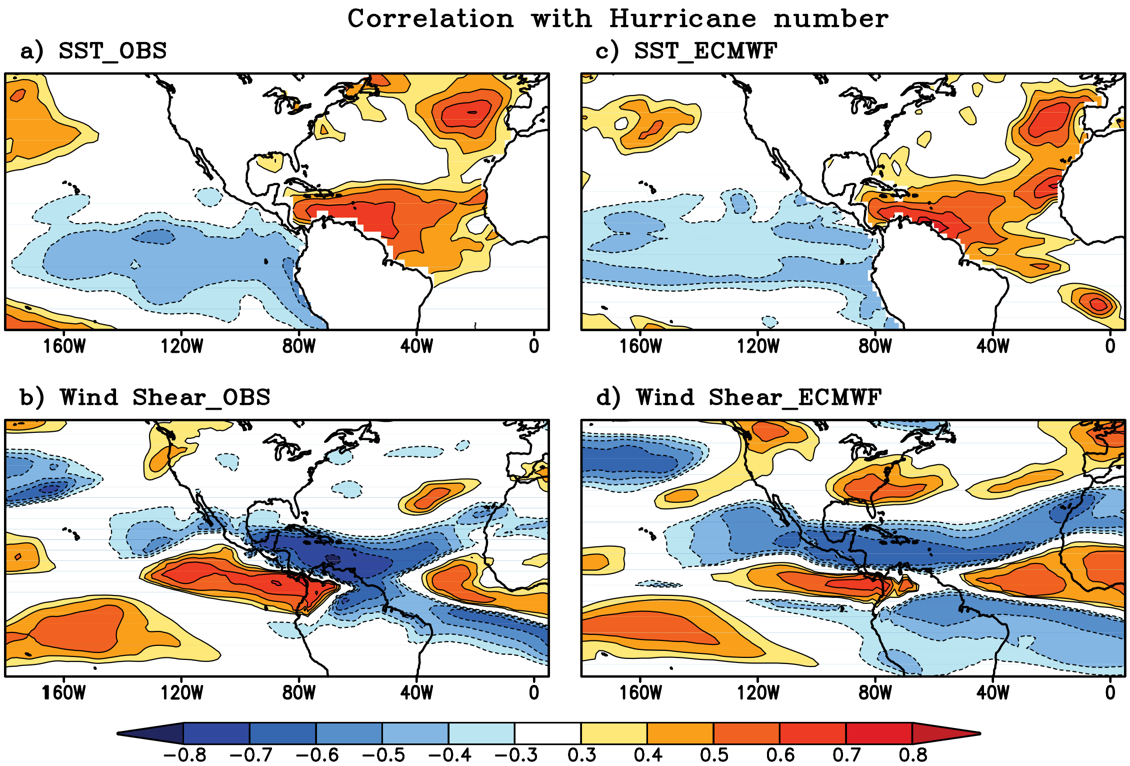

Figure 1. The spatial distribution of correlation coefficients between the inter-annual variation of the actual number of hurricanes and the (top) anomalous SST and (bottom) wind shear in (a, b) observation and (c, d) ensemble mean of the ECMWF hindcasts formed from July to October anomalies generated with July 1st initial condition.

atmospheric and land surface are obtained from the ERA-40. The initial conditions for the oceanic component are provided by ECMWF oceanic data assimilation system [*Balmaseda*, 2005]. In the ECMWF Seasonal Forecasting System, on the 1st day of each calendar month eleven ensemble members of 7-month duration were generated during the period from 1981 to 2006. The number of ensemble members increased to 41 from 2007 to 2009. Large-scale ocean-atmosphere predictors were formed from July-October (June-October) SST and wind anomalies generated with July (June) 1st initial conditions for the 29-year period (1981–2009).

3. Numerical-Empirical Forecast for Seasonal Hurricane Activity

[6] Predictors from ECMWF forecasts are selected based on their empirical relationship with the observed number of hurricanes. Figure 1 shows the correlation coefficient of the inter-annual variation between the observed number of hurricanes in the NATL and both SST and wind shear anomalies from observation (Figures 1a and 1b) and from ECMWF hindcasts (Figures 1c and 1d).

[7] Significant negative correlations are found between the observed East Pacific SST anomaly and NATL hurricane number (Figure 1a). This relationship has been well documented and related to ENSO variability and the subsequent modulation of vertical wind shear in the MDR [*Gray*, 1984; *Shapiro*, 1987; *Bell and Chelliah*, 2006; *Camargo et al.*, 2007; *Kim et al.*, 2009]. Seasonal hurricane activity is closely related to variations in NATL SST variations in the MDR [*Goldenberg et al.*, 2001; *Saunders and Lea*, 2008] and to the north between 30°N and 50°N [*Goldenberg et al.*, 2001; *Kossin and Vimont*, 2007]. These patterns are similar to the Atlantic Meridional Mode (AMM) that has been shown to be strongly related to the seasonal hurricane activity on both interannual and decadal timescales [*Kossin and Vimont*, 2007; *Vimont and Kossin*, 2007]. The decrease of wind shear magnitude over the MDR related to AMM variability (Figure 1b) induces an increase of seasonal hurricane activity. *Kossin and Vimont* [2007] show further that the combined positive SST anomaly is related to a decrease in shear during a positive AMM phase

Table 1. Correlation Coefficients Between the Time Series of Observed and Predicted Seasonal Hurricanes[a]

	SH	MS	NAS	SH+MS	SH+N3	MS+N3	MS+NAS	SH+NAS	SH+MS+NAS
CORR	0.6	0.56	0.61	0.65	0.58	0.62	0.62	0.74	0.70

[a]The predictors are; the North Atlantic SST (NAS; 330°E–350°E, 35°–45°N), MDR SST (MS; 280°E–310°E, 5–15°N), the SST over the Nino 3 region (N3; 210°E–270°E, 5°S–5°N), and vertical wind shear over the MDR (SH; 260°E–320°E, 10°–20°N). The limiting value of significant correlation coefficient is 0.47 at the 99% level.

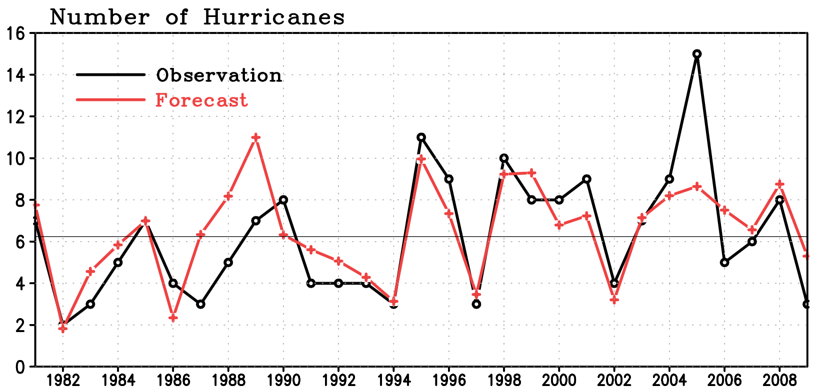

Figure 2. Number of hurricanes from observation (open circle) and forecast model (cross). The gray thin line is the average of the observation over 29-yr. The correlation coefficient between two time series is 0.741.

and creates a favorable environment for hurricane genesis. The interannual variability of the time series between the number of hurricane and the AMM SST index (http://www.esrl.noaa.gov/psd/data/timeseries/monthly/AMM) is highly correlated at 0.76 over the 29-year period.

[8] The correlation between the ensemble mean of the ECMWF hindcasts and observed seasonal hurricanes (Figures 1c and 1d) are similar to those found with observed data but with differences arising from model bias. While the negative correlation over the tropical Pacific is weaker than observed, the positive correlation in the North Atlantic SST is stronger and more extensive. Based on these relationships, based on the 11-member ensemble mean, we select three potential predictors from SST; the North Atlantic SST (NAS; 330°E–350°E, 35°–45°N), the MDR SST (MS; 280°E–310°E, 5–15°N), and the SST over the Niño 3 region (N3; 210°E–270°E, 5°S–5°N). A fourth potential predictor is the vertical wind shear over the MDR (SH; 260°E–320°E, 10°–20°N). The hurricane number correlates with the NAS, MDR, N3 and SH indices at 0.68, 0.61, −0.48 and −0.81, respectively, all exceeding the 99% significance level of 0.47. In summary, wind shear and both SST indices over the Atlantic are highly correlated to the seasonal hurricanes while the Niño 3 is more weakly correlated than the others.

[9] To forecast the interannual variability of seasonal hurricanes, sensitivity tests are performed using the four potential predictors singularly or in combination. To build an empirical relationship, a multiple or simple linear-regression model is constructed between the predictors and the observed number of hurricanes. A cross-validation method (leaving one-year out) is applied to obtain the regression parameters. Then the parameters are applied to the predictors of the target year to obtain seasonal forecasts of hurricane number. It should be noted that such a cross-validation method could artificially overestimate forecast skill [*DelSole and Shukla*, 2009]. Table 1 shows the prediction skill of seasonal hurricanes using the regression model. Although the prediction skill hovers around 0.6 when only one of the predictors is used, it improves to >0.7 when two predictors are combined (e.g., SH, NAS, and SH +NAS case) with the best combination of predictors coming from a combination of SH and NAS. Including the Niño 3 SST or the MDR SST does not increase the skill score significantly because the information they impart may be redundant having already been included in the vertical wind shear. As a result, we use both the MDR wind shear and the North Atlantic SST as predictors.

[10] Figure 2 shows the hybrid seasonal forecast of NATL hurricane number from 1981 to 2009. It forecasts a higher number of hurricanes than observed in the period from 1987 to 1989 but a lower number during the most active year of 2005. However, in 1995 and 1998, when the number of hurricanes was near 10, the model performs quite well. In addition, during the strong warm phase years of ENSO, 1982 and 1997, the deficiency of hurricane activity was well forecast due to the characteristic reduction in MDR wind shear [*Kim et al.*, 2009]. The correlation and root mean square error (RMSE) between the observation and the forecast is 0.74 and 2.05 over the period. This compares favorably to the CSU forecasts issued one month later in early August (http://typhoon.atmos.colostate.edu) with their values of 0.58 and 2.12 for the period 1984 to 2008. It should be mentioned that the additional skill of hybrid forecast might come from the fact that the empirical model is trained over a time period where the hurricanes happens to be especially highly correlated to environmental conditions. An important question is whether the hybrid scheme does better than the parent fully-dynamic ECMWF system? The ECMWF system during the 1990–2009 period, using data provided by Dr. F. Vitart (personal communication), ECMWF has a correlation with observed NATL hurricanes of 0.59 and a RMSE of 2.76 for hurricanes forming after August 1. It would appear that there is added value in the statistical rendering of the numerical model results. The Poisson regression model [*Elsner and Schmertmann*, 1993] does not outperform the linear regression model in the hybrid forecast (Figure S1 of the auxiliary material).[1]

[11] The prediction skill of the hybrid forecast system is competitive and often better than other schemes. Table 2 compares the actual number of total hurricanes to the forecasts issued by the following groups during late July or early August: CSU, NOAA (http://www.cpc.noaa.gov/products/outlooks/hurricane-archive.shtml), Tropical Storm Risk (referred to as TSR, http://www.tropicalstormrisk.com), CFS hybrid forecast (method 1 [*Wang et al.*, 2009]) and ECMWF forecast for the 8 years from 2002 to 2009. In these models, the predictand is the same: the total number

[1]Auxiliary materials are available in the HTML. doi:10.1029/2010GL044792.

Table 2. The Verification and Forecasts of Hurricane Frequency by Several Forecast Models From 2002 to 2009[a]

Year Issue	OBS	Hybrid Jul (Jun) IC	CFS Jul–Aug IC	CSU Early Aug	NOAA Early Aug	TSR Early Aug	ECMWF Jun
2002	4	3 (3)	4	4	4–6	4	5
2003	7	7 (8)	7	8	7–9	7	8
2004	9	8 (7)	7	7	6–8	8	5
2005	15	9 (9)	11	10	9–11	11	8
2006	5	7 (8)	9	7	7–9	8	13
2007	6	7 (7)	9	8	7–9	8	7
2008	8	9 (8)	9	9	7–10	10	9
2009	3	5 (4)	5	4	3–6	7	4
RMSE		2.45 (2.57)	2.50	2.24	2.41	2.50	4.09
		29yr: 2.05 (2.10)		25yr: 2.12			20yr: 3.62

[a]Numbers are rounded to the nearest integer. RMS errors are on the bottom. Hybrid forecasts with June initial condition are listed in parentheses.

of hurricanes in a season. We also compare the hybrid forecast and the ECMWF dynamical forecast issued in June for the period July to December. The numbers are rounded to the nearest integer. The RMSE of each forecast is listed at the bottom of the table. The relatively high RMS error in ECMWF forecast comes from one-month gap between the target period (JASOND) and the initial condition (June). To compare our hybrid forecast with ECMWF, hybrid forecasts with June initial condition are listed in parentheses. Other models (Table S1) with different predictand or not run in predictive mode are not part of this comparison.

[12] By using the total 41 ensemble members available during 2007, a probability forecast of hurricane occurrence can be made [*Vitart et al.*, 2007]. To make the forecast for 2007, the ECMWF prediction from 1981 to 2006 has been used to establish the empirical relationship between the hurricane number and the ensemble mean forecasts of MDR wind shear and North Atlantic SST. For the 2008 forecast, data was used from 1981 through 2007 and etc. Figure 3 shows the probability density that fits a normal distribution of the forecasts generated by the hybrid model in comparison with the others forecasts. For 2007 and 2008, the hybrid model shows a close relationship between the actual number of hurricanes compared to other forecasts. In 2009, the hybrid system fails principally because the numerical climate model forecast weaker wind shear than observed.

[13] Using predictors forecast from the June and July initial conditions, the hybrid seasonal hurricane forecasting system predicts 9 hurricanes for the summer of 2010. The greater than average number of hurricanes comes mainly from the weak wind shear anomaly over the MDR accompanied by strong La Niña condition. However, the normal SST over the eastern North Atlantic appears to restrain a further increase in hurricane number.

4. Conclusion and Discussion

[14] A hybrid forecast model for the seasonal North Atlantic hurricane activity is developed using a combination of numerical and empirical models. The empirical relationship is built on the number of seasonal hurricane occurrences relative to the variability of large-scale variables from 29-year ECMWF hindcasts for the hurricane season. The increase of seasonal hurricane activity correlates with a decrease of SST anomaly over the tropical East Pacific, an increase of SST anomaly over the MDR and North Atlantic

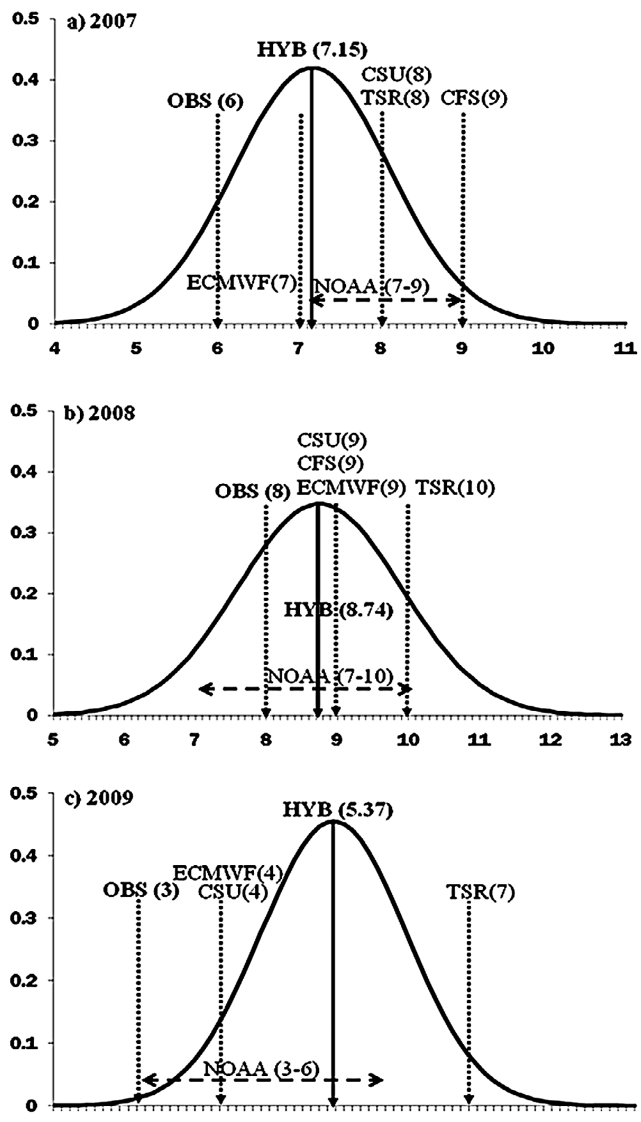

Figure 3. Probability density of predicted number of hurricanes in (a) 2007, (b) 2008 and (c) 2009 by hybrid model (HYB), CFS, CSU, NOAA, TSR and ECMWF with the actual hurricane number from observation (OBS).

and the decrease of wind shear over the MDR. The prediction shows the highest skill when both the North Atlantic SST and the MDR vertical wind shear are used as predictors.

[15] Through cross-validation over a 29-yr period, the forecast skill is competitive with forecasts currently available. In addition to demonstrating competitive skill relative to other forecast systems, the forecast is available one month earlier than the other forecasts that could provide information for the end-users, especially those who live in coastal regions. Moreover, with the advent of increased ensemble numbers in the seasonal forecast system, probabilistic forecast of North Atlantic hurricane numbers becomes more plausible after 2007 (Figure 3). We plan to extend the hybrid system to other parts of the tropics especially the North Pacific.

[16] Finally, noting the sensitivity of hurricane activity with a combination of climate oscillators, such as AMM, AMO, NAO, or Pacific Decadal Oscillation (PDO), there is an increasing need to understand how these oscillations are interlinked and how they influence hurricane activity [*Kossin et al.*, 2010; *Villarini et al.*, 2010]. Additional skill may arise by considering the slowly varying climate signals as predictors of the seasonal hurricane activity.

[17] **Acknowledgments.** We thank Dr. Frederic Vitart of ECMWF for providing us the ECMWF hurricane forecasts. We also thank Dr. Hui Wang of NOAA for providing us the 2009 forecast. This research has been supported in part by Climate Dynamics Division of the National Sciences Foundation under award NSF-ATM 0531771 and 0826909 and the Georgia Institute of Technology Foundation.

References

Anderson, D., T. Stockdale, M. Balmeseda, L. Ferranti, F. Vitart, F. Molteni, F. Doblas-Reyes, K. Mogensen, and A. Vidard (2007), Development of the ECMWF seasonal forecast System 3, *Tech. Memo. 503*, Eur. Cent. for Medium-Range Weather Forecasts, Reading, U. K. (Available at http://www.ecmwf.int/publications/library/do/references/show?id=87744)

Balmaseda, M. A. (2005), Ocean analysis at ECMWF: From real-time ocean initial conditions to historical ocean reanalysis, *ECMWF Newsl.*, *105*, 24–42.

Bell, G. D., and M. Chelliah (2006), Leading tropical modes associated with interannual and multidecadal fluctuations in North Atlantic hurricane activity, *J. Clim.*, *19*, 590–612, doi:10.1175/JCLI3659.1.

Berrisford, P., D. Dee, K. Fielding, M. Fuentes, P. Kallberg, S. Kobayashi, and S. Uppala (2009), *The ERA-interim archive*, ERA Rep. Ser. 1, Eur. Cent. for Medium-Range Weather Forecasts, Reading, U. K.

Camargo, S. J., K. A. Emanuel, and A. H. Sobel (2007), Use of a genesis potential index to diagnose ENSO effects on tropical cyclone genesis, *J. Clim.*, *20*, 4819–4834, doi:10.1175/JCLI4282.1.

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

Elsner, J. B. (2003), Tracking hurricanes, *Bull. Am. Meteorol. Soc.*, *84*, 353–356, doi:10.1175/BAMS-84-3-353.

Elsner, J. B., and C. P. Schmertmann (1993), Improving extended-range seasonal predictions of intense Atlantic hurricane activity, *Weather Forecast.*, *8*, 345–351, doi:10.1175/1520-0434(1993)008<0345:IERSPO>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.

Goldenberg, S. B., C. W. Landsea, A. M. Mestas-Nunez, and W. M. Gray (2001), The recent increase in Atlantic hurricane activity: Causes and implications, *Science*, *293*, 474–479, doi:10.1126/science.1060040.

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.

Holland, G. J., and P. J. Webster (2007), Heightened tropical cyclone activity in the North Atlantic: Natural variability or climate trend?, *Philos. Trans. R. Soc. A*, *365*, 2695–2716, doi:10.1098/rsta.2007.2083.

Kim, H. M., P. J. Webster, and J. A. Curry (2009), Impact of shifting patterns of Pacific Ocean warming events on North Atlantic tropical cyclone, *Science*, *325*, 77–80, doi:10.1126/science.1174062.

Klotzbach, P. J. (2007), Revised prediction of seasonal Atlantic basin tropical cyclone activity from 1 August, *Weather Forecast.*, *22*, 937–949, doi:10.1175/WAF1045.1.

Kossin, J. P., and D. J. Vimont (2007), A more general framework for understanding Atlantic hurricane variability and trends, *Bull. Am. Meteorol. Soc.*, *88*, 1767–1781, doi:10.1175/BAMS-88-11-1767.

Kossin, J. P., S. J. Camargo, and M. Sitkowski (2010), Climate modulation of North Atlantic hurricane tracks, *J. Clim.*, *23*, 3057–3076, doi:10.1175/2010JCLI3497.1.

Landsea, C. W. (2005), Hurricanes and global warming, *Nature*, *438*, E11–E12, doi:10.1038/nature04477.

Landsea, C. W., et al. (2004), The Atlantic hurricane database re-analysis project: Documentation for the 1851–1910 alterations and additions to the HURDAT database, in *Hurricanes and Typhoons: Past, Present, and Future*, edited by R. J. Murname and K.-B. Liu, pp. 177–221, Columbia Univ. Press, New York.

Pielke, R. A., and C. W. Landsea (1998), Normalized hurricane damages in the United States: 1925–95, *Weather Forecast.*, *13*, 621–631, doi:10.1175/1520-0434(1998)013<0621:NHDITU>2.0.CO;2.

Saunders, M. A., and A. S. Lea (2008), Large contribution of sea surface warming to recent increase in Atlantic hurricane activity, *Nature*, *451*, 557–560, doi:10.1038/nature06422.

Shapiro, L. J. (1987), Month-to-month variability of the Atlantic tropical circulation and its relationship to tropical storm formation, *Mon. Weather Rev.*, *115*, 2598–2614, doi:10.1175/1520-0493(1987)115<2598:MTMVOT>2.0.CO;2.

Smith, T. M., and R. W. Reynolds (2004), Improved extended reconstruction of SST (1854–1997), *J. Clim.*, *17*, 2466–2477, doi:10.1175/1520-0442(2004)017<2466:IEROS>2.0.CO;2.

Uppala, S. M., et al. (2005), The ERA-40 re-analysis, *Q. J. R. Meteorol. Soc.*, *131*, 2961–3012, doi:10.1256/qj.04.176.

Villarini, G., G. A. Vecchi, and J. A. Smith (2010), Modeling of the dependence of tropical storm counts in the North Atlantic basin on climate indices, *Mon. Weather Rev.*, *138*, 2681–2705, doi:10.1175/2010MWR3315.1.

Vimont, D. J., and J. P. Kossin (2007), The Atlantic meridional mode and hurricane activity, *Geophys. Res. Lett.*, *34*, L07709, doi:10.1029/2007GL029683.

Vitart, F., M. R. Huddleston, M. Déqué, D. Peake, T. N. Palmer, T. N. Stockdale, M. K. Davey, S. Ineson, and A. Weisheimer (2007), Dynamically-based seasonal forecasts of Atlantic tropical storm activity issued in June by EUROSIP, *Geophys. Res. Lett.*, *34*, L16815, doi:10.1029/2007GL030740.

Wang, H., et al. (2009), A Statistical forecast model for Atlantic seasonal hurricane activity based on the NCEP dynamical seasonal forecast, *J. Clim.*, *22*, 4481–4500, doi:10.1175/2009JCLI2753.1.

Webster, P. J., G. J. Holland, J. A. Curry, and H.-R. Chang (2005), Changes in Tropical Cyclone Number, Duration, and Intensity in a Warming Environment, *Science*, *309*(5742), 1844–1846.

H.-M. Kim and P. J. Webster, School of Earth and Atmospheric Science, Georgia Institute of Technology, 311 Ferst Dr., Atlanta, GA 30332, USA. (pjw@eas.gatech.edu)