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

Hye-Mi Kim and Peter J. Webster
School of Earth and Atmospheric Science,
Georgia Institute of Technology, Atlanta, Georgia

July 2010
Submitted to *GRL*

---

* *Corresponding author address*:
Peter J. Webster, Georgia Institute of Tech., 311 Ferst Dr., Atlanta, Georgia, 30332
E-Mail: pjw@eas.gatech.edu

Abstract

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. An empirical relationship is built on the number of seasonal hurricane and the large-scale variables from ECMWF hindcasts based on a 29-yr (1981-2009) dataset. The increase of seasonal hurricane activity correlates with a negative sea surface temperature (SST) anomaly over the tropical East Pacific, a positive SST anomaly over the Main Development Region (MDR) and North Atlantic, and a 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 at least competitive or better than most publicly-available forecast models but made one month earlier lead-time. The hybrid model initialized at June and July 2010 forecasts the 2010 hurricane season active with 9 hurricanes.

1. Introduction

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, 1999*], there has been a growing demand for extended seasonal forecasts of hurricane activity with lead times of months. Although the hurricane activity is related directly to local thermodynamic conditions [*Goldenberg et al. 2001; Saunders and Lea 2008*], a large portion of hurricane activity 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; Camargo et al. 2009; Kim et al. 2009; Klotzbach 2010; Kossin et al. 2010]*. Noting these associations, most hurricane forecasts are based on empirical relationships between the hurricane activity, sea surface temperature 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 ENSO, sea surface temperature (SST) over the east Atlantic, sea level pressure (SLP) variability over the tropical Atlantic and the statistics of storms that have occurred 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. There has been some success with this methodology. For example, *Vitart et al.* [2007] shows substantial skill compared to purely empirical forecasts with the EUROSIP (EUROpean Seasonal to Inter-annual Prediction) multi-model ensemble of coupled ocean atmosphere models.

We pose the hypothesis that a combination of the two methodologies may provide additional skill beyond that of the component models. Here we propose and test a new hybrid system combining the ECMWF System 3 coupled ocean-atmosphere climate model (Anderson et al. 2007) and an empirical linear regression model. In a sense, it is a Bayesian system where the statistical priors are adjusted by forecasts of the predictors from the numerical climate model. *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. *Wang et al* [2009] provide competitive skill with current empirical forecast models. Section 2 introduces details of the numerical and empirical models and observation data. Section 3 examines the prediction skill of seasonal hurricane activity and section 4 summarizes the results with discussion.

2. Data and analysis

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, a period that matches the forecast reanalysis data set for the ECMWF System 3. The predictand for the hybrid system is the number of hurricanes over the Atlantic. 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. However, forecasts based on June data will also be documented. 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 set [*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.

The ECMWF hindcasts are used to provide predictors in the hybrid forecast model. Initial conditions for the atmospheric and land surface were obtained from the ERA-40. The initial conditions for the oceanic component are provided by ECMWF oceanic data assimilation system [*Balmaseda et al. 2005*]. The details of ECMWF Seasonal Forecasting System used in this study are described at site (http://www.ecmwf.int/products/forecasts/seasonal/documentation/system3). In the ECMWF Seasonal Forecasting System, on the 1st day of each calendar month eleven ensemble members of 7-month duration were generated on the 1st day of each month 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 SST and wind anomalies generated with July 1st initial condition from the 29 years (1981-2009).

3. Numerical-empirical forecast for seasonal hurricane activity

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 (Figs 1a, b) and from ECMWF forecasts (Figs 1c, d).

Significant negative correlations are found between the observed East Pacific SST anomaly and NATL hurricane number (Fig. 1a). This relationship has been well documented [*Gray 1984; Tang and Neelin 2004; Bell and Chelliah 2006; Kim et al. 2009*] and related to ENSO variability and the subsequent modulation of vertical wind shear in the MDR. 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 30ºN and 50ºN [*Goldenberg et al. 2001; Kossin and Vimont 2007*]. These patterns are similar to the Atlantic Meridional Mode (AMM) and 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*]. Related to the AMM variability, the decrease of wind shear magnitude over the MDR (Fig. 1b) induces an increase of seasonal hurricane activity. *Kossin and Vimont* [2007] show further that the combined positive SST anomaly related decrease in shear during a positive AMM phase creates an overall favorable environment for hurricane genesis. The interannual variability of time series between the number of hurricane and the AMM SST index is highly correlated at 0.76 over the 29 year period (Table 1). AMM SST index is calculated through projecting SST onto the spatial structure resulting from the maximum covariance analysis to SST (http://www.esrl.noaa.gov/psd/data/timeseries/monthly/AMM).

The correlations between ECMWF hindcasts and observed seasonal hurricanes (Fig. 1c, d) are similar to those found with observed data 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, from the 11-member ensemble mean, we select three potential predictors from SST; the North Atlantic SST (NAS; 330ºE-350ºE, 35º-45ºN), MDR SST (MS; 280ºE-310ºE, 5-15ºN), and the SST over the Nino 3 region (N3; 210º-270ºE, 5ºS-5ºN). A fourth potential predictor is the vertical wind shear over the MDR (SH; 260º-320ºE, 10º-20ºN). 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 Nino 3 is relatively weakly correlated than the others. To forecast the interannual variability of seasonal hurricanes, sensitivity tests are performed using the four potential predictors singularly or in combination. A multiple or simple linear-regression model is constructed between the predictors and the observed number of hurricanes to build an empirical relationship. 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. 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 comes from a combination of SH and NAS. Including the Nino 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. *Wang et al.* [2009] found that the highest skill occurred when MDR wind shear is used as the only predictor from the CFS seasonal forecast.

Figure 2 shows the seasonal forecast of NATL hurricane number from 1981 to 2009 using the hybrid model. It forecasts a higher number 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 strong El Nino signal in the 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 compared to the CSU forecasts) issued one month later in early August (http://typhoon.atmos.colostate.edu) with values of 0.58 and 2.12 for the period 1984 to 2008. Does the hybrid scheme do better than the parent ECMWF system? The ECMWF system during the 1990-2009 period, using data provided by F. Vitart, 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 prediction skill of the hybrid forecast system is fairly competitive and often better than other scheme, even though our model issues forecasts one month prior to the other publicly-available seasonal forecasts. Table 2 compares the actual number of hurricanes and the forecasts issued at 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. For a fair comparison with other forecast schemes, we use the ECMWF forecast issued in June which forecasts the hurricane number over the period July to December. The numbers are rounded to the nearest integer and 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 of 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.

By using the total 41 ensemble members available during 2007, a probability forecast of hurricane occurrence can be made. 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 form 1981 though 2007 and etc.. Figure 3 shows the probability density of the forecasts generated by the hybrid model as well as a comparison with the others forecasts. For 2007 and 2008 case, the hybrid model shows a close relationship to the actual number compared to the other forecasts. In 2009 the system fails principally because the numerical climate model forecast weaker wind shear than observed.

Table 1: Correlation coefficients between the time series of observed and predicted seasonal hurricanes. The predictors are; the North Atlantic SST (NAS; 330ºE-350ºE, 35º-45ºN), MDR SST (MS; 280ºE-310ºE, 5-15ºN), the SST over the Nino 3 region (N3; 210º-270ºE, 5ºS-5ºN), and vertical wind shear over the MDR (SH; 260º-320ºE, 10º-20ºN). The limiting value of significant correlation coefficient is 0.47 at the 99% level.

	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

Table 2. The verification and forecasts of hurricane frequency by several forecast models from 2002 to 2009. Numbers are rounded to the nearest integer. RMS errors are on the bottom. Hybrid forecasts with June initial condition are listed in parentheses.

YEAR	**OBS**	**Hybrid**	**CFS**	**CSU**	**NOAA**	**TSR**	**ECMWF**
Issue		Jul (Jun) IC	Jul-Aug IC	Early Aug	Early Aug	Early Aug	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**

Table 3: Correlation coefficients between the time series of observed climate indices (AMM, AMO and NINO3 index) and number of hurricanes from 1970 to 2009.

	Jan	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**JASO**
AMM	0.32	0.33	0.23	0.28	0.37	0.46	0.57	0.66	0.7
AMO	0.43	0.46	0.46	0.47	0.52	0.54	0.54	0.57	0.55
NINO3	-0.02	-0.07	-0.08	-0.11	-0.23	-0.3	-0.27	-0.32	-0.37

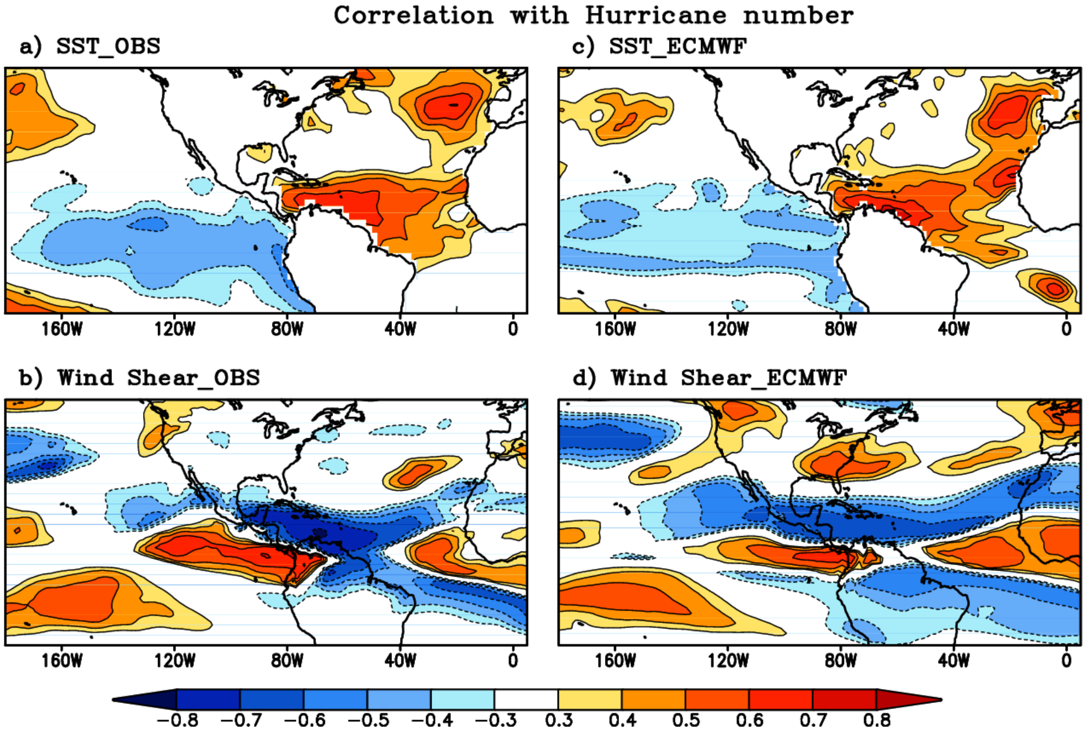


Figure 1: The spatial distribution of correlation coefficients between the inter-annual variation of the actual number of hurricanes and both SST (top) and wind shear (bottom) anomalies in (a), (b) observation and (c), (d) ECMWF forecasts of ensemble mean.

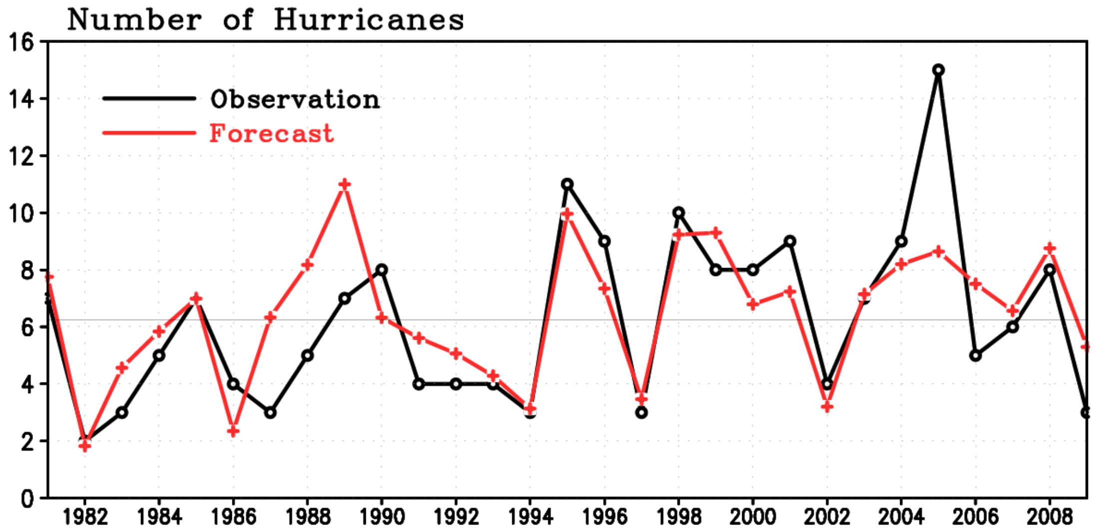


Figure 2: Number of hurricanes for observation (open circle) and forecast model (cross). The gray thin line is the average of the observation over 29-yr. The correlation coefficient between two time series is 0.741.

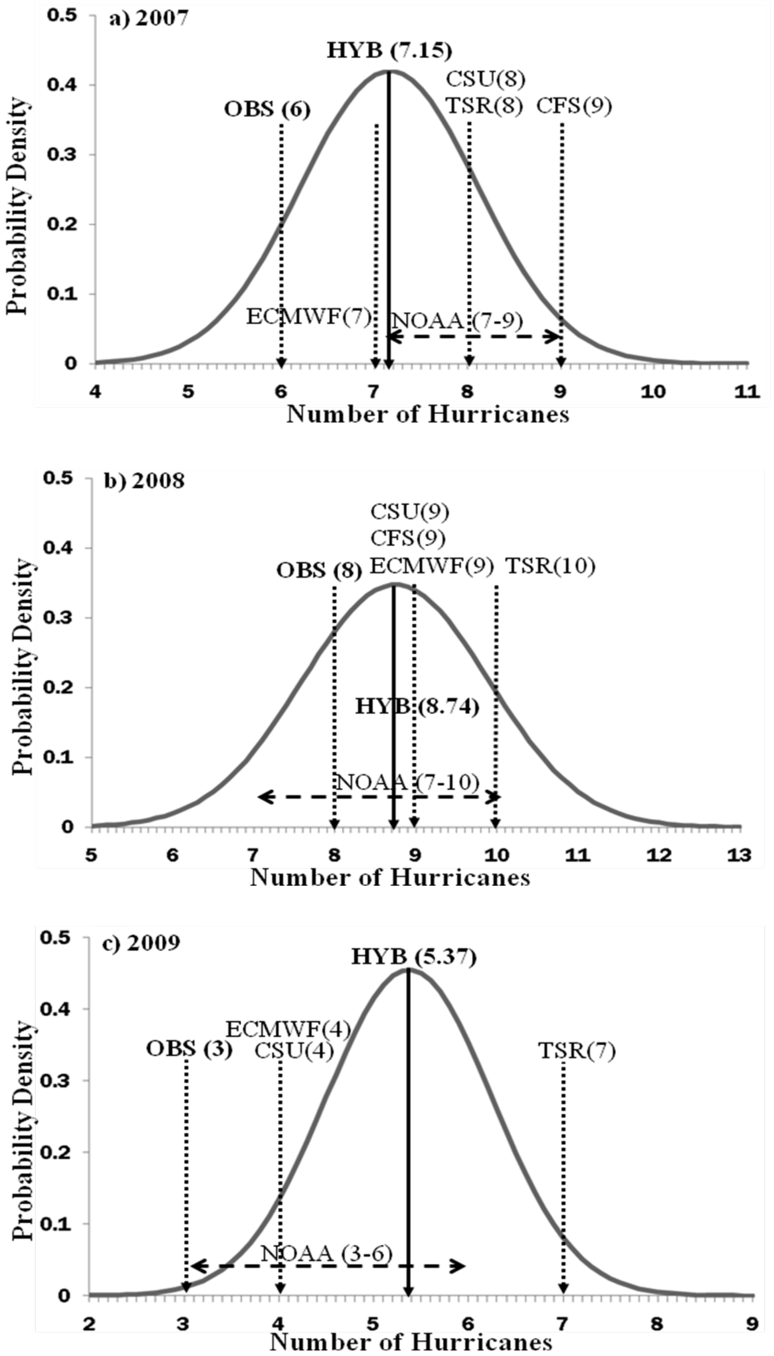
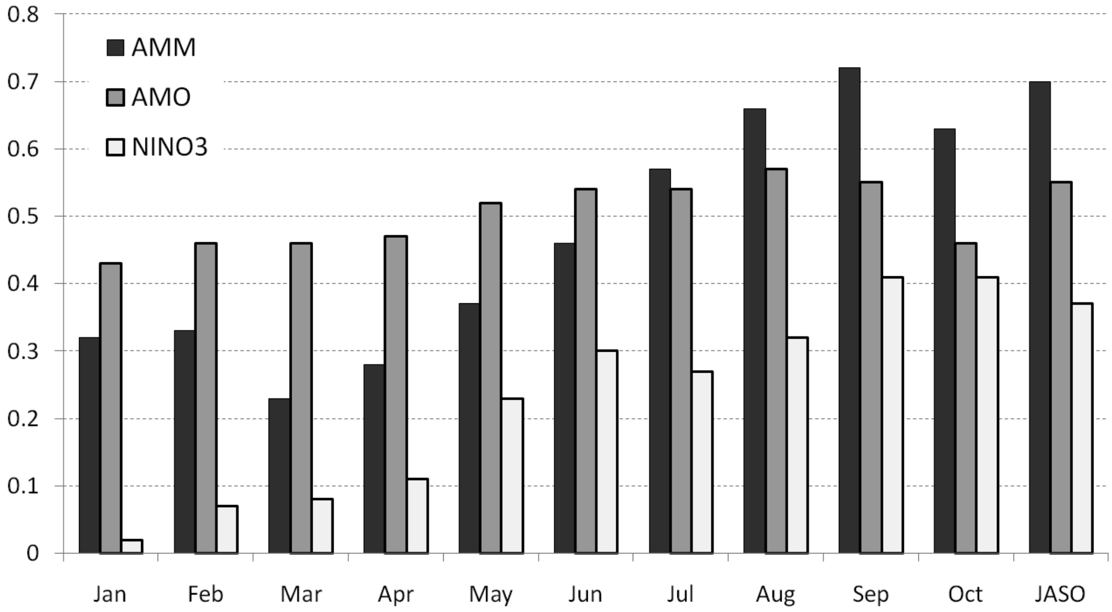


Figure 3: Probability density of predicted number of hurricanes in a) 2007, b) 2008 and c) 2009 by hybrid model (HYB), CFS, CSU, NOAA, TSR and ECMWF with the actual hurricane number from observation (OBS).



Using predictors from June and July initial condition, the hybrid seasonal hurricane forecasting system predicts 9 hurricanes for 2010 summer. The above normal number of hurricanes mainly comes from the weak wind shear anomaly over the MDR accompanied by strong La Nina condition. The normal SST over the eastern North Atlantic restrains the increase of number.

4. Conclusion and discussion

A forecast model for the seasonal North Atlantic hurricane activity is developed using a combined numerical and empirical techniques. The empirical relationship is built on the number of seasonal hurricane occurrences relative to large-scale variables from 29-year (1981-2009) ECMWF hindcasts for the June to October season. The large-scale ocean and atmosphere numerical product is related statistically to the seasonal North Atlantic hurricane activity which is similar to that observed. 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 and the decrease of wind shear over the MDR. These large-scale structures of favorable conditions for hurricanes are close to those found for the positive phase of AMM. Using these four predictors from the hindcasts, sensitivity tests were performed for the seasonal hurricane activity forecast. The prediction shows the highest skill when both the North Atlantic SST and the MDR vertical wind shear are used as predictors.

Through the cross-validation over a 29-yr period, the forecast skill shows at least competitive with forecasts currently available. In addition to being competitive skill with other forecast systems, the forecast is available one month earlier than the other forecasts that could provide useful information for the end-users, especially those who live in coastal regions. Moreover, with the advent of increased ensemble numbers, probabilistic forecast of North Atlantic hurricane number has been attempted by using extension of ensembles after 2007 (Figure 3). We plan to extend the hybrid system to other parts of the topics especially the North Pacific.

Another issue that needs to be explored is the influence of multi-decadal and inter-annual climate variability on the tropical cyclone activity. Figure 4 (or Table 3) shows the correlation coefficients between the time-series of climate indices (AMM, AMO and NINO3) and seasonal hurricane number from 1970 to 2009. The information of the El Nino condition in previous season does not provide additional information for the upcoming seasonal hurricane activities. The AMM is highly correlated with seasonal hurricane number but it is not significant before June. In contrast, the AMO and hurricanes are significantly correlated as early as the previous winter and does not change as much as the AMM through the previous winter to summer. These relationships can be explained by the different timescales of climate variability as by *Vimont and Kossin* [2007]. Hurricane activity is related to the AMM on both interannual and decadal timescales, while it is related to the AMO only on a decadal timescale. Therefore, additional skill may be coming from considering the slowly varying climate signals as a predictor for predicting the seasonal hurricane activity. Note that the NINO 3 correlations are non-existent prior to the mid-spring in concert with the existence of a spring predictability barrier [*Webster and Yang 1992; Webster 1995*]. The combination of climate oscillation, such as AMM, AMO, NAO, or Pacific Decadal Oscillation (PDO) needs to be understood in order to interpret how these oscillations are linked to each other and influence the tropical cyclone activity. Such a study will provide additional information for further improvement of the forecast models that use as input the fluctuations of large-scale climate variability.

Acknowledgements

We thank Frederic Vitart of ECMWF for providing us the ECMWF hurricane forecasts. We also thank 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. We are indebted to the European Centre for Medium Range Weather Forecasts for access to the System 3 seasonal forecast archives.

References

Anderson, D., Stockdale, T., Balmeseda, M., Ferranti, L., Vitart, F., Molteni, F., Doblas-Reyes, F., Mogensen, K. & Vidard, 2007: *Development of the ECMWF seasonal forecast System 3. ECMWF Technical memorandum 503*. (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 Newsletter, No. 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. Climate*, **19**, 590-612.

Berrisford, P., D. Dee, K. Fielding, M. Fuentes, P. Kallberg, S. Kobayashi and S. Uppala (2009), The ERA-Interim archive, *ERA report series.*

Camargo, S. J, M. C. Wheeler, and A. H. Sobel (2009), Diagnosis of the MJO Modulation of tropical cyclogenesis using an empirical index, *J. Atmos. Sci.,* **66**, 3061-3074.

Elsner, J. B. (2003), Tracking hurricanes, *Bull. Amer. Meteor. Soc.,* **84**, 353-356.

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

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.

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

Holland, G. J. and P. J. Webster (2007), Heightened tropical cyclone activity in the North Atlantic: natural variability or climate trend? *Phil. Trans. R. Soc*. A, 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.

Klotzbach, P. J. (2007), Revised prediction of seasonal Atlantic basin tropical cyclone activity from 1 August. *Wea. Forecasting,* **22**, 937-949.

Klotzback P. J. (2010), On the Madden-Julian oscillation-Atlantic hurricane relationship. *J. Climate*, **23**, 282-293.

Kossin J. P., and D. J. Vimont (2007), A more general framework for understanding Atlantic hurricane variability and trends, *Bull. Amer. Meteor. Soc,* **88**, 1767-1781.

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

Landsea, C. W., and Coauthors (2004), The Atlantic hurricane database re-analysis project: Documentation for the 1851-1910 alterations and additions to the HURDAT database. *Hurricanes and Typhoons: Past, Present and Future,* R. J. Murname and K.-B. Liu, Eds., Columbia University Press, 177-221.

Landsea, C. W. (2005) Hurricanes and global warming. *Nature,* **438**, E11–E13.

Palmer and Coauthors (2004), Development of a European multimodel ensemble system for seasonal-to-interannual prediction (DEMETER). *Bull. Am. Meteor. Soc.,* **85**, 853–872.

Pielke, R. A., and C. W. Landsea (1999) El Nino, La Nina and Atlantic hurricane damage in the United States. *Bull. Amer. Meteor. Soc.,* **42**, 2027-2033.

Pielke, R. A., and C. W. Landsea (1998), Normalized hurricane damages in the United States: 1925-95. *Weath. Fore.* **13**, 621-631.

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.

Smith, T. M. and R. W. Reynolds, (2004), Improved extended reconstruction of SST (1854-1997), *J. Climate*, **17**, 2466–2477.

Tang B. H., and J. D. Neelin (2004), ENSO influence on Atlantic hurricanes via tropospheric warming. *Geophys. Res. Lett.,* **31**, L24204, doi:10.1029/2004GL021072.

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.

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., and Coauthors (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., and Coauthors (2009), A Statistical Forecast Model for Atlantic Seasonal Hurricane Activity Based on the NCEP Dynamical Seasonal Forecast, *J. Climate,* **22**, 4481-4500.

Webster, P. J., (1995), The annual cycle and the predictability of the tropical coupled ocean-atmosphere system. *Meteor. Atmos. Phys.,* **56,** 33-55.

Webster, P. J. and S. Yang (1992), Monsoon and ENSO: Selectively Interactive Systems. *Quart. J. Roy. Meteor. Soc.,* **118**, 877-926.