Chapter Seven

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7. Seasonal Forecasting of Tropical Cyclones

7.1 Introduction

Not long ago, scientists only dreamed of making confident and reliable seasonal hurricane forecasts. These dreams are now a reality, thanks to tremendous technological increases over the last thirty years along with an improved knowledge of the global climate system. The first seasonal hurricane forecasts for the North Atlantic basin were issued in 1984 (Gray 1984b), and by 2007, seasonal forecasts had expanded to include every major hurricane region in the world (see Table 7.1, adapted from Camargo et al. 2007a). Several of the seasonal forecasts are discussed in this chapter, while the others are briefly discussed in Camargo et al. (2007a).

Table 7.1. Agencies that issue forecasts for various tropical cyclone basins.

	North Atlantic	Eastern North Pacific	Central North Pacific	Western North Pacific	Australia Region	North Indian Ocean	South Indian Ocean	South Pacific Ocean
City University of Hong Kong, China				x Statistical				
Colorado State University, USA	x Statistical							
Cuban Meteorological Institute, Cuba	x Statistical							
European Centre for Medium-Range Weather Forecasts, England	x Dynamical	x Dynamical		x Dynamical	x Dynamical	x Dynamical	x Dynamical	x Dynamical
International Research Institute for Climate and Society, USA	x Dynamical	x Dynamical		x Dynamical	x Dynamical			x Dynamical
Macquarie University, Australia					x Statistical			x Statistical
National Meteorological Service, Mexico		x Statistical						
National Climate Centre, China				x Statistical				
NOAA Climate Prediction Center, USA	x Statistical	x Statistical	x Statistical					
Tropical Storm Risk, England	x Statistical			x Statistical	x Statistical			

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Several technological advances were needed before seasonal hurricane forecasts could become widespread. One advance came in the form of a major reanalysis project carried out in 1996 by the U.S. National Atmospheric and Oceanic Administration (NOAA) and the National Center for Atmospheric Research (NCAR) (Kalnay et al. 1996). The NCEP/NCAR reanalysis project, utilizing a sophisticated global climate model, produced homogeneous and global datasets of wind, pressure, and temperature at 6-hourly intervals dating back to 1948. For the first time, the available climate record was no longer plagued by discontinuities that occurred each time an improved data analysis package and numerical forecast model was implemented.

Another major advance came with the development of global climate models which were used not only to do the reanalysis but also to provide near real-time updates of global climate conditions. Now, ever-improving technologies such as satellites, computers, land-based observation systems, and model-based forecasts and analyses are routinely used by forecasters and researchers throughout the world.

But more than just better data and technology were needed before a seasonal hurricane outlook could be made. Fundamental breakthroughs in our understanding of the dominant climate factors influencing seasonal hurricane activity were also needed. The first major breakthrough came in 1984 with the pioneering research of Dr. William Gray, who discovered that the El Niño / Southern Oscillation (ENSO) strongly influenced year-to-year fluctuations in Atlantic hurricane activity (Gray 1984a,b). Using this research, Gray made the first seasonal Atlantic hurricane outlook in that same year at Colorado State University (CSU), and his team has been issuing outlooks ever since.

Another breakthrough came in the 1990's when scientists established that multi-decadal fluctuations in Atlantic hurricane activity were more than simply a random collection of above-normal or below-normal seasons. Instead, they were explained by predictable, large-scale climate factors that included multi-decadal fluctuations in Atlantic SSTs (called the Atlantic Multi-decadal Oscillation, Gray et al. 1996, Landsea et al. 1999) and the West African monsoon system (Hastenrath 1990, Gray 1990, Landsea and Gray 1992, Landsea et al., 1992, Goldenberg and Shapiro 1996).

Utilizing the reanalysis dataset, Bell and Chelliah (2006) showed that inter-annual and multi-decadal extremes in Atlantic hurricane activity resulted from a coherent and inter-related set of atmospheric and oceanic conditions associated with the leading modes of tropical climate variability. These modes were shown to be directly related to fluctuations in tropical convection, thereby linking Atlantic hurricane activity, West African monsoon rainfall, and Atlantic sea-surface temperatures, to tropic-wide climate variability. Based on this work, NOAA's Climate Prediction Center (CPC) began issuing seasonal Atlantic hurricane outlooks in August 1998, followed by seasonal East Pacific outlooks in 2004. At the same time, forecasters throughout the world were developing seasonal hurricane predictions for other major hurricane regions (Table 7.1).

Seasonal hurricane outlooks are based on either statistical, dynamical, or a blend of statistical and dynamical, procedures. Both the statistical and dynamical approaches bring a wide spectrum of forecast techniques to bear on the seasonal hurricane forecast problem. Some techniques are purely objective. Others are a subjective blend of selected statistical and dynamical techniques. Regardless of the technique or the way the forecast is communicated, seasonal hurricane forecasts are all probabilistic in nature. Forecasters try to give the best estimate of the likely (most probable) upcoming activity, while at the same time recognizing there are uncertainties inherent in all seasonal forecast techniques.

Three main statistical techniques are presently in use. One approach first utilizes statistical regression equations to predict the likely strength of key atmospheric and oceanic anomalies. This is done by either directly predicting their strength, or by first predicting the dominant climate patterns that strongly control their strength. A second set of regression equations is then used to predict the likely seasonal activity associated with the expected anomalies.

A second and complementary statistical approach utilizes a climate-based binning technique, wherein the historical distribution of activity associated with the predicted climate conditions is isolated. This climate-based analog approach allows the forecaster to focus only on those seasons having similar climate conditions, and differs from the pure regression equations that are often derived using all seasons and therefore all sets of climate conditions.

A third statistical approach developed by NOAA for use in their 2008 forecasts utilizes regression equations that relate coupled ocean-atmosphere dynamical climate model forecasts of key atmospheric and oceanic anomalies to the observed seasonal activity. In this way, dynamical predictions can be utilized to forecast the upcoming seasonal activity without a direct count of the exact number of named storms and hurricanes produced by the model. A second dynamical approach is to directly count the number of named storms a given climate model predicts (e.g., Vitart et al. 1997, Camargo et al. 2005).

Although seasonal hurricane forecasts have expanded greatly in recent years, there are many long-term challenges ahead. Some challenges are related to the observed hurricane data itself. In many regions, accurate hurricane records do not exist before satellites became widespread in the 1970s. In the Atlantic, more accurate records date back to the late 1940s with the beginning of aircraft reconnaissance.

Other challenges involve developing long-term statistical regression equations from reanalysis data that extends back only to 1948. Also, there are biases within the Reanalysis itself, which are related to the evolution of observing systems in recent years (Ebisuzaki et al. 1997, Kistler et al. 2001). These include global satellite coverage, extensive buoy placements in the Pacific and Atlantic Ocean, and an expanded radiosonde network in tropical regions.

Still other forecast challenges are related to accurate dynamical seasonal predictions of the key circulation and sea-surface temperature anomalies. While dynamical models have improved tremendously in recent years, they all contain large biases and errors that limit their use. For example, one major forecast uncertainty inherent to all climate models is tropical convection.

Yet, two dominant climate factors influencing seasonal Atlantic hurricane activity (ENSO and the Multi-decadal signal), which are also leading modes of tropical variability, are both intimately linked to changing large-scale patterns of tropical convection. ENSO predictions are especially critical, as ENSO has been shown to have a dramatic impact on tropical cyclone activity around the globe. As a result, ENSO predictions remain a main source of uncertainty for seasonal hurricane forecasts.

Another uncertainty common to all forecast techniques is weather patterns that are unpredictable on seasonal time scales, yet can sometimes develop and last for weeks or months, possibly affecting seasonal hurricane activity. A third source of forecast uncertainty is that the numbers of named storms and hurricanes can sometimes vary considerably for the same set of climate conditions. For example, one cannot know with certainty whether a given set of climate conditions will be associated with several short-lived storms or fewer longer-lived storms with greater intensity.

Making seasonal hurricane landfall forecasts is perhaps the most sought-after goal of seasonal hurricane forecasters. Unfortunately, an ongoing consequence of these challenges and uncertainties is the present very limited ability to make such forecasts accurately, confidently, and reliably. Compounding the challenge is the fact that hurricane landfalls are largely determined by the weather patterns in place at the time the hurricane approaches, which are generally not predictable more than 5-7 days in advance.

Hurricane experts and emergency management officials throughout the world know that hurricane disasters can occur regardless of the activity within a season. They encourage residents, businesses, and government agencies of coastal and near-coastal regions to prepare for every hurricane season regardless of the seasonal outlook. It only takes one hurricane (or even a tropical storm) to cause a disaster.

In the next few sections, several of the seasonal forecast methodologies currently in use for forecasting tropical cyclone activity in various basins around the globe are discussed in detail. Several other forecast methodologies are also discussed in Camargo et al. (2007a).

7.2 Colorado State University seasonal hurricane outlooks

Colorado State University (CSU) has been issuing seasonal predictions of Atlantic basin tropical cyclone activity since 1984 (Gray 1984a, b). These forecasts are issued at four lead times prior to the active part of the Atlantic basin hurricane season: in early December, in early April, in early June and in early August. Real-time forecasts of named storms in early June have correlated at 0.57 with observations over the period from 1948-2007. The statistical models utilized by the CSU forecast team to make their predictions have undergone considerable modifications in recent years. Instead of attempting to individually hindcast indices such as named storms, named storm days, major hurricanes, etc., they have developed a technique that shows significant skill at hindcasting Net Tropical Cyclone (NTC) activity (Gray et al. 1994) and then empirically deriving these other indices from the NTC prediction. Also, for the early April, June and August techniques, earlier seasonal forecasts are weighted at 50%, 50% and 40%, respectively when developing the final forecast (Figure 7.1). In the next few paragraphs, each forecast will be briefly discussed, with references provided for more extensive discussion.

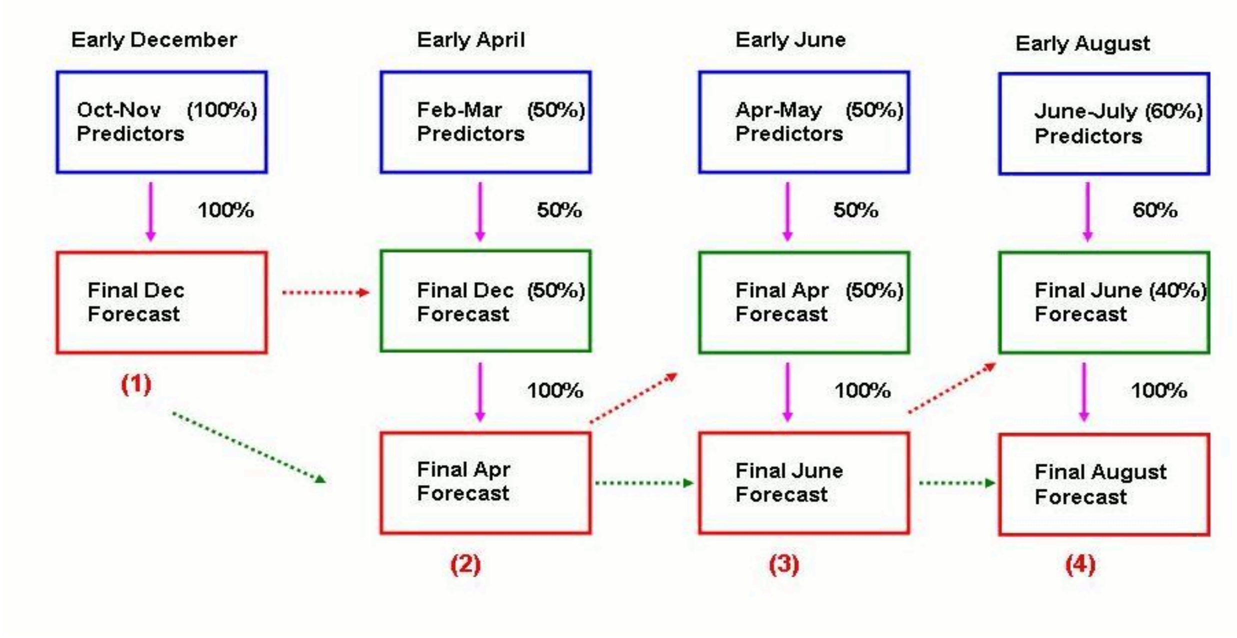

Figure 7.1. The new methodology utilized by CSU in calculating statistical forecasts of seasonal NTC.

December forecast

Initial predictions of seasonal hurricane activity from early December were issued by Gray and colleagues in December 1991 for the 1992 hurricane season (Gray et al. 1992). This model has undergone significant revisions since it was initially developed (Klotzbach and Gray 2004). Following the unsuccessful seasonal hurricane forecasts of the past few years, a new December forecast model has been developed (Klotzbach 2008). This model, as is done with the April, June and August models, was built over the period from 1950-1989 and then the equations developed over the period from 1950-1989 were tested on the years from 1990-2007 to determine if the model showed similar levels of skill in the more recent period. Table 7.2 displays the current predictors utilized in the new December statistical model.

Table 7.2. Listing of current early December predictors. A plus (+) means that positive values of the parameter indicate increased hurricane activity during the following year.

Predictor	Location
1) October-November SST (+)	(55-65°N, 60-10°W)
2) November 500 hPa geopotential height) (+)	(67.5-85°N, 50°W-10°E)
3) November SLP (+)	(7.5-22.5°N, 175-125°W)

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The forecast is created by combining the three December predictors using least-squared linear regression over the period from 1950-2007. The resulting hindcasts are then ranked in order from 1 (the highest value) to 58 (the lowest value). The final NTC hindcast was obtained by taking the final December NTC hindcast rank and assigning the observed NTC value for that rank. For example, if the final December NTC hindcast rank was 10 (the 10th highest rank), the NTC value assigned for the prediction would be the 10th highest observed rank, which in this case would be 166 NTC units. Final hindcast values are constrained to be between 40 and 200 NTC units. When the rank prediction model is utilized, 54% of the variance in NTC is hindcast over the period from 1950-2007.

April forecast

April forecasts are currently issued using a similar methodology to what was used in early December (Klotzbach and Gray 2008a). Two February-March predictors were selected that explained a considerable amount of variability in NTC (Table 7.3). These predictors were then ranked and combined with the early December prediction to come up with a final seasonal NTC hindcast. 64% of the variance in NTC is hindcast over the period from 1950-2007 using the April hindcast model.

Table 7.3. Listing of current early April predictors. A plus (+) means that positive values of the parameter indicate increased hurricane activity.

Predictor	Location
1) February-March SST Gradient (+)	(30-45°N, 30-10°W) - (30-45°S, 45-20°W)
2) March SLP (-)	(10-30°N, 30-10°W)
2) Early December Hindcast (+)	

June forecast

Early June forecasts are currently issued using two April-May predictors combined with the early April hindcast values (Klotzbach and Gray 2008b) (Table 7.4). 66% of the variance in NTC is hindcast over the period from 1950-2007 using the June hindcast model.

Table 7.4. Listing of current early June predictors. A plus (+) means that positive values of the parameter indicate increased hurricane activity.

Predictor	Location
1) Subtropical Atlantic Index (+): April-May SST (+) & May SLP (-)	(20-50°N, 30-15°W) (10-35°N, 40-10°W)
2) April-May 200 hPa U (-)	(5-25°S, 50-90°E)
3) Early June Hindcast (+)	

August forecast

A final seasonal forecast update is issued in early August, prior to the climatologically most active part of the Atlantic hurricane season. The new August statistical model utilizes a combination of four predictors which show significant skill back to the start of the 20th century (Table 7.5) (Klotzbach 2007). When these predictors are combined with the early June hindcast, approximately 65% of the post-1 August variance in NTC activity can be explained. Brief descriptions of how each predictor likely impact Atlantic basin hurricane activity follow.

Table 7.5. Listing of current early August predictors. A plus (+) means that positive values of the parameter indicate increased hurricane activity.

Predictor	**Location**
1) June-July SST (+)	(20-40°N, 35-15°W)
2) June-July SLP (-)	(10-20°N, 60-10°W)
3) June-July SST (-)	(5°S-5°N, 150-90°W)
4) Before 1 August Tropical Atlantic Named Storm Days (+)	(South of 23.5°N, East of 75°W)
5) Early June Hindcast (+)	

Discussion

The revised statistical models developed by CSU over the past several years put more of an emphasis on understanding physical links between individual predictors and Atlantic tropical cyclone activity. Also, the new models have been developed over the period from 1950-1989, leaving aside the past 18 years for quasi-independent testing. The more concrete physical links combined with increased statistical rigor should lead to improved skill in future years.

7.3 NOAA seasonal hurricane outlooks

NOAA began issuing probabilistic seasonal outlooks for the North Atlantic hurricane region in 1998 and for the East and Central North Pacific regions in 2004. The Atlantic and East Pacific outlooks are an official product of the Climate Prediction Center, made in collaboration with the National Hurricane Center and Hurricane Research Division. The Central Pacific outlook is an official product of the Central Pacific Hurricane Center, made in collaboration with the CPC. The Atlantic hurricane seasonal outlook is issued in late May, and updated in early August to coincide with the onset of the peak months (August-October, ASO) of the season. A single seasonal outlook is issued in late May for the East and Central North Pacific regions.

NOAA's seasonal hurricane outlooks indicate the likely (approximately a two-thirds chance) seasonal range of named storms, hurricanes, and major hurricanes, along with the most probable season type. The Atlantic and East Pacific outlooks also indicate probabilities for each season type (above-, near-, or below-normal), along with the likely range of total seasonal activity as measured by the ACE (Accumulated Cyclone Energy) index which is a measure of the combined number, intensity, and duration of tropical storms, subtropical storms and hurricanes (Bell et al. 2000). The outlooks are designed to provide the public with a general guide to the expected overall nature of the upcoming hurricane season. They are not seasonal hurricane landfall forecasts, and do not imply levels of activity for any particular region.

NOAA's seasonal hurricane outlooks are based primarily on predicting the combined impacts of three dominant climate factors: ENSO (Gray 1984a), the Atlantic multi-decadal oscillation (Gray et al. 1996, Landsea et al. 1999), and the tropical multi-decadal signal (Bell and Chelliah 2006). Each of these factors has strong links to recurring rainfall patterns along the equator, and together they produce the inter-related set of atmospheric and oceanic conditions typically associated with both seasonal and multi-decadal fluctuations in Atlantic hurricane activity (Fig. 7.2). For the August update, additional predictive information is also used, such as anomalous early season activity, and atmospheric and oceanic anomalies that may have developed which are not related to the dominant climate predictors.

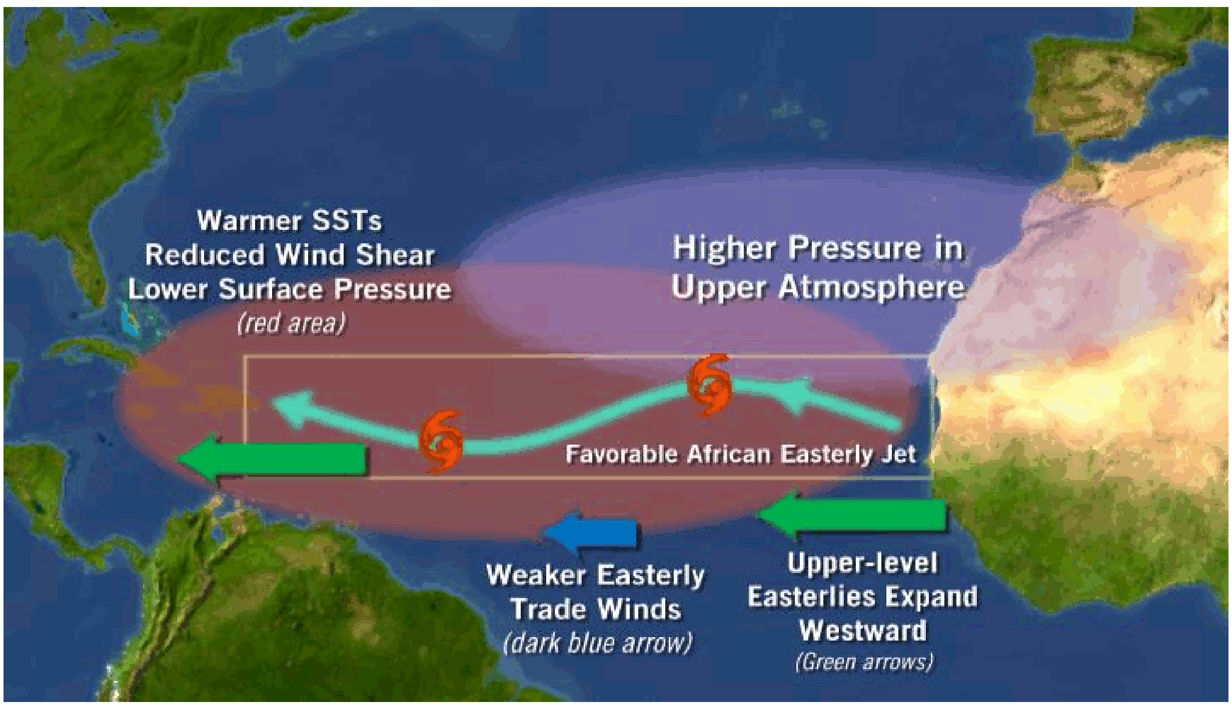

Figure 7.2. Schematic of atmospheric and oceanic anomalies during August-October (ASO) associated with active Atlantic hurricane seasons and eras.

ENSO reflects year-to-year fluctuations in tropical convection across the equatorial Pacific Ocean, and mainly influences hurricane activity for a single season at a time. The Atlantic multi-decadal oscillation reflects changes in Atlantic SSTs in both the tropics and high latitudes, and is associated with both above-normal and below-normal active hurricane eras that historically last 25-40 years. The tropical multi-decadal signal is the leading multi-decadal mode of tropical convective variability (Bell and Chelliah (2006), and captures the observed link between the Atlantic multi-decadal oscillation and an east-west seesaw in anomalous convection between the West African monsoon region (Hastenrath 1990, Gray 1990, Landsea and Gray 1992, Landsea et al., 1992, Goldenberg and Shapiro 1996), and the Amazon Basin (Chen et al. 2001, Chu et al. 1994).

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NOAA's seasonal Atlantic hurricane outlooks reflect a subjective blend of three main statistical forecasting techniques. One technique utilizes regression equations for the period 1971-2007 to first establish the relationship between seasonal activity and the combined effects of ENSO, the tropical multi-decadal signal, and tropical Atlantic sea-surface temperatures. Then, forecasts of these climate factors are used to predict the upcoming seasonal activity. Such a procedure inherently assumes the climate forecast is perfect, which is generally not the case of course. Therefore, in practice the forecaster uses a regression-based contingency table for each parameter (shown here for ACE, Table 7.6), which yields a likely range of activity given reasonable uncertainties in the climate prediction itself.

Table 7.6. Contingency table showing regressed seasonal ACE (Accumulated Cyclone Energy) values associated with an active Atlantic phase of the tropical multi-decadal signal for varying strengths of ENSO and tropical Atlantic sea-surface temperature anomalies.

Tropical Atlantic Sea-surface Temperature Anomalies (°C)							
		-0.50	**-0.25**	**0**	**0.25**	**0.50**	**0.75**
El Niño	Strong	5.7	33.0	60.3	87.6	114.9	142.2
	Moderate	22.2	49.5	76.8	104.1	131.4	158.7
	Weak	38.7	66.0	93.3	120.6	148.0	175.3
	Neutral	55.2	82.6	109.9	137.2	164.5	191.8
La Niña	Weak	71.8	99.1	126.4	153.7	181.0	208.3
	Moderate	88.3	115.6	142.9	170.2	197.5	224.8
	Strong	104.8	132.1	159.4	186.8	214.1	241.4

A chart showing the historical distribution of regression errors (Fig. 7.3) is used to quantify uncertainties in the regression technique itself. For example, the regression equation explains 67% of the seasonal ACE variance.The absolute regression error in ACE is less than 20 percent of the median (meaning a highly accurate forecast) in 27% of seasons, and less than 40 percent of the median in two-thirds (67%) of seasons. Therefore, in practice NOAA assigns a range of at least ±40 percent of the median to the predicted seasonal ACE.

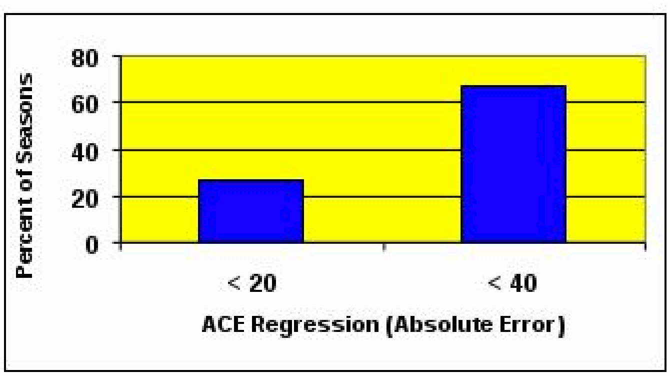

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Figure 7.3. Percentage of seasons with an absolute error in the regressed seasonal ACE (Accumulated Cyclone Energy) less than 20 and less than 40 percent of the median. The absolute error is less than 20 percent of the median in about one-fourth of the seasons, and less than 40 percent of the median in about two thirds of the seasons. The regression period is 1971-2007. The predictors are ENSO, the tropical multi-decadal signal, and tropical Atlantic sea-surface temperatures.

The regression results also help the forecaster to better quantify the usefulness of the technique through an error analysis of the predicted season types. It is found that perfect predictions of the above climate factors correctly predict the Atlantic hurricane season type approximately 80% of the time. However, a one-category forecast error in season type (e.g., an above-normal season is predicted but a near-normal season is observed) is seen on average every 5-6 years. A two-category forecast error (e.g., a below-normal season is predicted but the season is above-normal) is seen on average every 12 years. Therefore, for the May outlook, the highest probability assigned to any season type is roughly 80%, and lowest probability is roughly 10%.

A second prediction technique is the climate-based analogue approach, whereby the forecaster focuses on the distributions of activity associated with past seasons having comparable climate signals to those being predicted. This approach also allows the forecaster to quickly and accurately determine the historical probabilities of the three season types associated with the predicted climate factors.

Another prediction technique (Wang et al. 2009) utilizes regression equations to first establish the relationship between the seasonal hurricane activity and dynamical model forecasts of atmospheric and oceanic conditions during ASO. The regression period is 1982-2007.The predictors in the regression equations are 60-member ensemble mean forecasts for each ASO period of vertical wind shear and Atlantic sea-surface temperatures, which are obtained from NOAA's coupled ocean-atmosphere climate model called the Global Forecast System (GFS). In practice, this technique is utilized to obtain the ensemble mean predicted seasonal activity, and the forecasted range of activity using the individual ensemble members. Using the individual members,the model probabilities of an above-, near-, and below-normal season are also derived. This technique is particularly appealing, because it avoids some of the very significant challenges associated with counting the actual number of named storms and hurricanes produced by a given climate model.

7.4 City University of Hong Kong seasonal hurricane outlooks

Introduction

Since 2000, the Laboratory for Atmospheric Research at City University of Hong Kong has been issuing real-time predictions of annual tropical cyclone (TC) activity over the western North Pacific (WNP)1. The predictands include the annual number of tropical storms and typhoons and the annual number of typhoons. These forecasts are issued in early April and early June prior to the active TC season, the latter serving as an update of the April forecast based on information in April and May. Verifications of the predictions have shown that the predictions are mostly correct within the error bars. These are all statistical predictions with predictors drawn from a large pool of indices that represent the atmospheric and oceanographic conditions in the previous year up to the spring of the current year. Details can be found in Chan et al. (1998, 2001) and Liu and Chan (2003).

April forecast

a. Predictors related to ENSO

Many studies have shown that El Niño/Southern Oscillation (ENSO) has an effect on TC activity in the year the ENSO event develops and the year after the ENSO event (Chan 2000; Wang and Chan 2002). Therefore, indices that can be used as proxies of ENSO may be good predictors of TC activity. In this forecast scheme, a few predictors are used to represent the ENSO status prior to the TC season and to predict the possible status during the TC season.

<u>Predictor 1. Niño3.4 index</u>

Niño3.4 index is the mean sea surface temperature anomalies in the NINO3.4 region (5°S-5°N, 170°-120°W) and is commonly used to represent the status of ENSO. In the April forecast, the Niño3.4 index from December of the previous year to January of the current year is included to reflect the ENSO status in the winter preceding the TC season. A winter associated with an El Niño (a La Niña) condition is generally followed by a less (more) active TC season. The Niño3.4 index in March of the current year is used to represent the current ENSO status.Subsequent changes of the Nño3.4 index also give the possible ENSO status during the TC season. If an El Niño (a La Niña) event develops during the TC season, the TC season tends to be more (less) active especially for the number of typhoons. This partly explains that the skill of prediction for the number of typhoons is higher than that of the number of tropical storms and typhoons using this predictor.

<u>Predictor 2. Equatorial Southern Oscillation Index (Equatorial SOI)</u>

The Equatorial Southern Oscillation Index (Equatorial SOI) is defined as the standardized anomaly of the sea-level pressure difference between the equatorial eastern Pacific (80°W-130°W, 5°N-5°S) and an area over Indonesia (90°E-140°E, 5°N-5°S). This predictor also acts as a proxy of ENSO and the principle involved is similar to that of Niño3.4 index. Note that this predictor is only used in the prediction of the number of typhoons.

b. Predictors related to atmospheric circulation

Indices that represent the conditions in winter and spring prior to the TC season are used. The changes in these conditions are related to subsequent changes during the TC season so that the indices can be proxies of the summertime environment. The indices considered include the westward extension of the 500-hPa subtropical ridge and the West Pacific index. All these indices are monthly values from April of the previous year to March of the current year.

<u>Predictor 3. West Pacific index</u>

The West Pacific (WP) pattern is a primary mode of low-frequency variability over the North Pacific in all months (Barnston and Livezey, 1987). During winter and spring, this pattern shows a north-south dipole of 500-hPa geopotential height anomalies, with one center over the Kamchatka Peninsula and another center of opposite sign over the WNP along 30°N.
The WP index in the months March and April of the current year is negatively correlated with TC activity. Positive values of this index indicate the positive phase of the WP pattern, which shows a north-south dipole of 500-hPa geopotential height anomalies, with positive anomalies over the WNP. This pattern is generally associated with a stronger subtropical high and a weaker monsoon trough in the peak TC season. Therefore a less active TC season is expected.

Predictor 4. Index of the westward extent of the subtropical high over the WNP

The index of the westward extent of the subtropical high over the WNP in the months February-May of the current year is positively correlated with TC activity. A lower value of this index indicates that the subtropical high extends more westward and is generally associated with a less active TC season. The values of this index in these months are correlated with the geopotential high anomalies during the peak TC season (July-October). Therefore, this index can represent the spring-time mid-level atmospheric conditions, which are related to subsequent changes of the subtropical high during the TC season which eventually affect the TC activity.

June forecast

The parameters used in the June forecast are similar to those in the April forecast. As mentioned in the Introduction, the June forecast makes use of monthly values in the months April and May of each predictor to provide the more up-to-date information about the atmospheric and oceanographic conditions. Such information is a reflection of these conditions during the TC season. Therefore the June forecast should have a higher skill than the April forecast.

7.5 Tropical Storm Risk seasonal hurricane outlooks

Tropical Storm Risk (TSR) has been issuing public outlooks for seasonal tropical cyclone activity since 2000. These outlooks are provided for the North Atlantic, Northwest Pacific and Australian regions (Table 7.7). The TSR forecasts are available for basin activity and for landfalling activity on the USA, Caribbean Lesser Antilles and Australia. Outlooks are issued in deterministic and tercile probabilistic form. The TSR forecast models are statistical in nature but are underpinned by predictors having sound physical links to contemporaneous tropical cyclone activity. These predictors and their physical mechanisms are described by region in the sections below. TSR provides, as part of their seasonal outlooks, the hindcast precision of each forecast parameter assessed over prior periods of at least 20 years. An example of TSR"s extended hindcast skill as a function of lead time is shown for Northwest Pacific typhoon activity (Figure 7.5).

Table 7.7. Summary of Tropical Storm Risk seasonal tropical cyclone outlooks.

TSR Seasonal Tropical Cyclone Outlooks					
Region	**Parameters forecast**	**Landfalling**	**Forecast issue times**	**Deterministic forecasts**	**Probabilistic forecasts**
North Atlantic	TS, H, IH, ACE (and for sub-regions)	United States TS, H, US ACE	Monthly from Dec to Aug	All parameters(basin and landfalling)	Basin ACE US ACE
Western North Pacific	TS, T, IT, ACE	-	Monthly from Mar to Aug	All parameters(basin and landfalling)	Basin ACE
Australian Region	TS, STC, ACE	Australia TS	Monthly from May to Dec	All parameters (basin and landfalling)	Basin TS Australia TS
TS = number of tropical storms; H = number of hurricanes; IH = number of intense hurricanes; ACE = Accumulated Cyclone Energy Index; US ACE = US Accumulated Cyclone Energy Index; T = number of typhoons; IT = number of intense typhoons; STC = number of severe tropical cyclones.					

Seasonal North Atlantic hurricane activity

TSR divides the North Atlantic into two regions: (a) the "tropical" North Atlantic comprising the North Atlantic south of 20°N, the Caribbean Sea and the Gulf of Mexico, and (b) the "extra-tropical" North Atlantic. 85-90% of the hurricanes and intense hurricanes that made landfall on the United States between 1950 and 2005 originated as tropical depressions in the "tropical" North Atlantic. TSR forecasts tropical cyclone activity in the "tropical" North Atlantic and uses a rolling prior 10-year climatology for tropical cyclone activity in the "extra-tropical" North Atlantic.

TSR outlooks for tropical cyclone activity in the "tropical" North Atlantic employ two predictors (Table 7.8 and Figure 7.4). These are: (1) The forecast speed of the trade winds which blow westward across the tropical Atlantic and Caribbean Sea in July, August and September. These winds influence cyclonic vorticity and vertical wind shear over the main hurricane track region. Cyclonic vorticity either helps or hinders the spinning up of storms depending upon its anomaly sign and magnitude. Vertical wind shear either helps or hinders a vertically coherent storm vortex from developing depending upon its magnitude; (2) The forecast temperature of sea surface waters between west Africa and the Caribbean where many hurricanes develop during August and September. Waters here provide heat and moisture to help power the development of storms within the hurricane main development region.

Seasonal US landfalling hurricane activity

TSR outlooks for US landfalling tropical cyclone activity issued between December and July employ a historical thinning factor between "tropical" North Atlantic activity and US landfalling activity.The TSR outlook issued in early August uses wind patterns (at heights between 750 and 7,500 metres above sea level) from six regions over North America and the east Pacific and North Atlantic oceans during July to predict the US ACE index (effectively the cumulative wind energy from all US striking tropical storms during the main hurricane season). Wind anomalies in these regions in July are indicative of persistent atmospheric circulation patterns that either favour or hinder evolving hurricanes from reaching US shores during August and September. The model correctly anticipates whether US hurricane losses are above-median or below-median in 74% of the years between 1950 and 2003 (Saunders and Lea 2005). It also performed very well in "real-time" operation in 2004 and 2005.

Table 7.8. Predictor(s) underpinning the Tropical Storm Risk seasonal outlooks by region.

TSR Seasonal Forecast Predictor(s)			
Region	**Basin or Landfalling**	**Predictor(s)**	**References**
North Atlantic	Basin	Forecast July-September trade wind speed over the Caribbean Sea and tropical North Atlantic [region 30°W-100°W, 7.5°N-17.5°N], and the forecast August-September sea surface temperature in the hurricane main development region [20°W-60°W, 10°N-20°N].	Lea and Saunders (2004) Lea and Saunders (2006b) Saunders (2006) Saunders and Lea (2008)
	US Landfalling	Historical thinning factors linking basin to US landfalling activity (Dec to July forecasts). July tropospheric wind anomalies between heights of 925mb and 400mb over North America, the east Pacific and the North Atlantic (Aug US ACE index forecast).	Saunders and Lea (2005)
Western North Pacific	Basin	Forecast August-September Niño 3.75 sea surface temperature [region 140°W-180°W, 5°S-5°N].	Lloyd-Hughes, Saunders and Rockett (2004) Lea and Saunders (2006a)
Australian Region	Basin	Forecast August-September Niño 3.75 sea surface temperature [region 140°W-180°W, 5°S-5°N].	Lloyd-Hughes, Saunders and Rockett (2004) Lea and Saunders (2006a)
	Australia Landfalling	Historical thinning factor linking basin to landfalling activity.	

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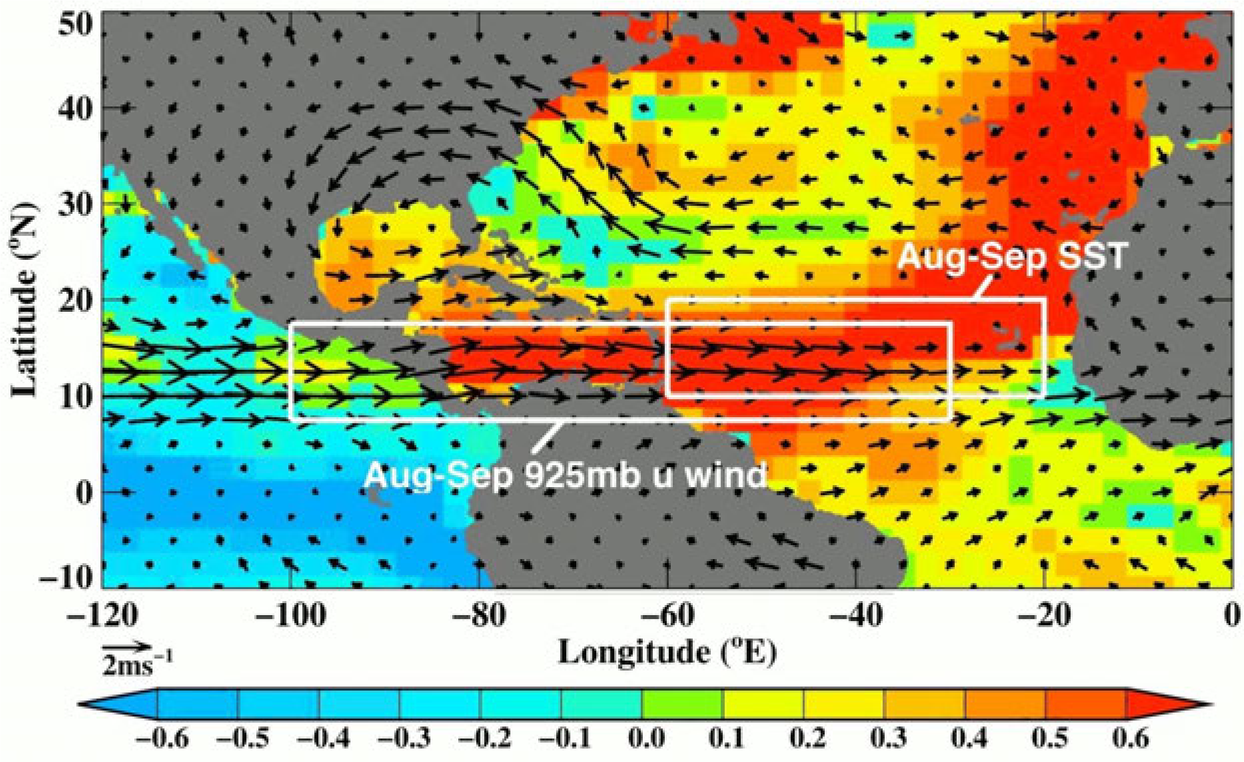


Figure 7.4. Physical nature of the TSR statistical model for "tropical" North Atlantic hurricane activity. The display shows the two August-September environmental field areas that comprise the model and the August-September anomalies in sea surface temperature (color coded in degrees Celsius) and 925mb wind anomalies (arrowed) linked to active Atlantic hurricane years. (Reproduced from Saunders and Lea 2008).

Seasonal Western North Pacific typhoon activity

The TSR predictors for Western North Pacific typhoon activity are as follows. Tropical storm and typhoon numbers are forecast before May using the Niño 3 SST from the prior September; from May they are forecast using April surface pressure over the region 17.5°N-35°N, 160°E-175°W. Intense typhoon numbers and the ACE index are forecast using the forecast value for the August-September Niño 3.75 region (5°S-5°N, 180°W-140°W) SST (Table 7.2). The latter is predicted using the consolidated CLIPER model described in Lloyd-Hughes et al. (2004). Above average (below average) Niño 3.75 SSTs are associated with weaker (stronger)TRADE winds over the region 2.5°N-12.5°N, 120°E-180°E. These in turn lead to enhanced (reduced) cyclonic vorticity over the Western North Pacific region where intense typhoons form.

Figure 7.5 displays the seasonal predictability of the Western North Pacific ACE index for the 41-year period 1965 to 2005. This period starts in 1965 as this marks the beginning of reliable Pacific typhoon wind records (Lea and Saunders 2006a). Hindcast skill is assessed using cross-validation with 5-year block elimination. Confidence intervals are computed using the standard bootstrap method (Effron and Gong 1983) with replacement. The Northwest Pacific ACE index has positive forecast skill to 95% confidence over the 41-year period from early May. Historically 95% of typhoons occur after the 1st May.

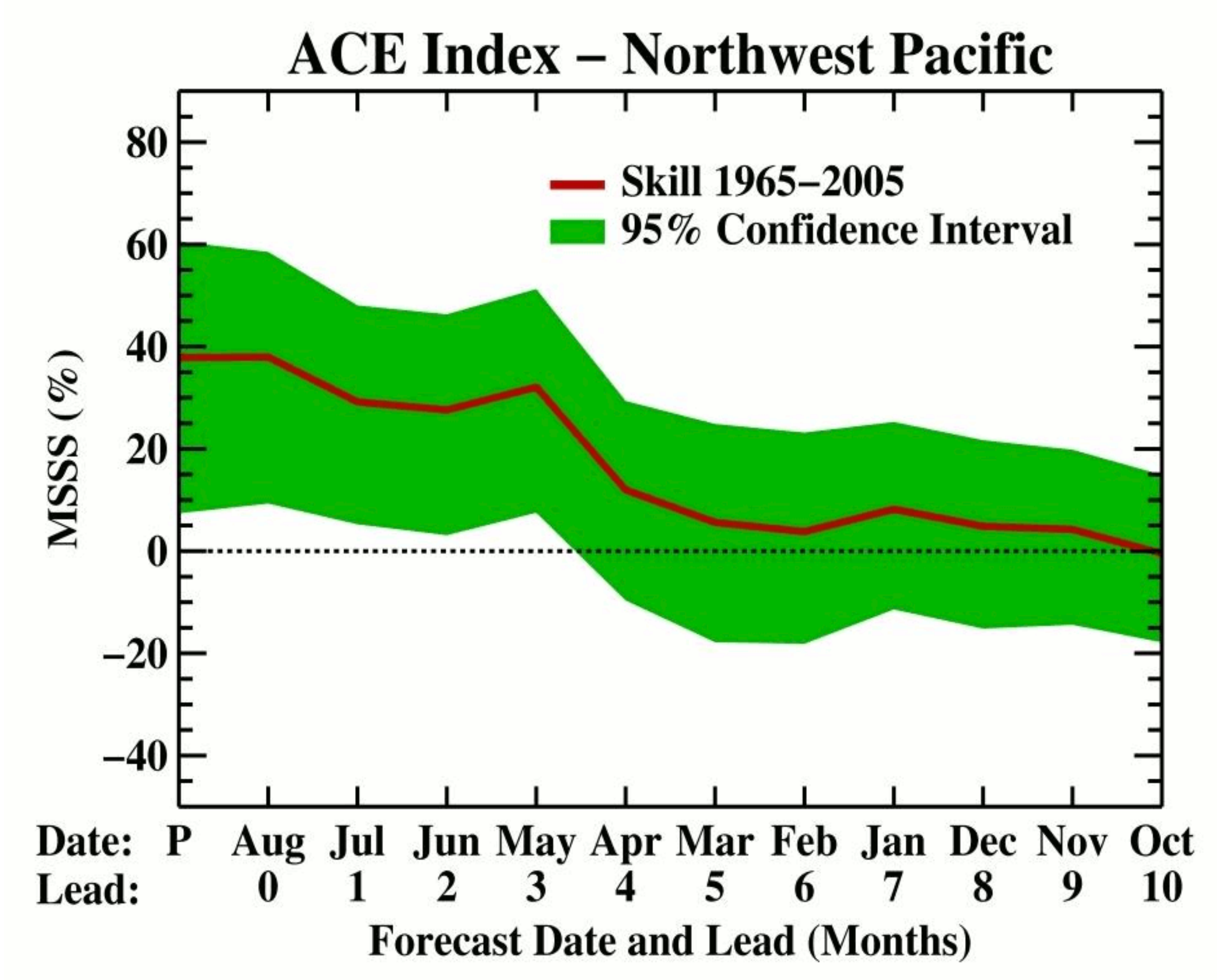


Figure 7.5. TSR hindcast seasonal prediction skill for the Northwest Pacific ACE index 1965-2005 shown for monthly leads from the previous October. Skill is displayed by the mean square skill score (MSSS) with 1965-2005 used as the climatology.

Seasonal Australian-region tropical storm activity

TSR defines the "Australian region" as encompassing the Southern Hemisphere region from 100°E to 170°E (a storm must form as a tropical cyclone within to count).The Australian tropical storm season spans the period from 1st November to 30th April. The TSR predictor for leads up to November is the forecast October-November Niño 4 SST (Table 7.2). The TSR December seasonal outlook employs the observed October-November Niño 4 SST. The Niño 4 SST forecasts are made with the consolidated CLIPER model reported by Lloyd-Hughes et al (2004). Early austral summer SSTs in the Niño 4 region influence Australian-region tropical storm activity by affecting atmospheric vertical wind shear over the Australian region during Austral summer. Cooler (warmer) than normal Niño 4 SST in October-November leads to below-average (above-average) atmospheric vertical wind shear which, in turn, favours above-average (below-average) tropical storm activity.

7.6 ECMWF seasonal hurricane outlooks

The European Centre for Medium-Range Weather Forecasts (ECMWF) has produced seasonal forecasts of tropical storm frequency since 2001. These forecasts are not publicly available. They are available only to ECMWF member states and World Meteorological Organization (WMO) members. Unlike the NOAA, CSU, City University of Hong Kong, and TSR statistical methods discussed above, the ECMWF seasonal forecasts of tropical storms are based on a dynamical method. They use the outputs of coupled Global Circulation Model (GCM) integrations to predict tropical cyclone activity. This method is based on the ability of GCMs to create tropical storm disturbances that have strong similarities to real-world tropical storms. For example, they develop a warm temperature anomaly over the centre of the vortex, which is a characteristic of observed tropical storms.

The ECMWF seasonal forecasting system 3 (Anderson et al. 2007) is based on a coupled GCM that has been extensively integrated for 7-months forecasts. The atmospheric component has a T159 spectral resolution (about 120 kilometer resolution). The model has 62 vertical levels with a model-top level located at about 5 hPa. The ocean model is the Hamburg Ocean Primitive Equation model (HOPE) with a resolution equivalent to 2° in the extra-tropics, but the resolution increases in the tropics to 0.5°. The ocean model has 29 vertical levels. Ocean initial conditions are provided by the ECWMF operational ocean analysis system (Balmaseda et al. 2007). The ocean and atmosphere are coupled directly, without flux correction, using the Ocean Atmosphere Sea Ice Soil (OASIS) coupler. The coupling frequency is 24 hours. The coupled system is integrated forward for 7 months from the initial conditions. In order to sample the uncertainty in the initial conditions and model formulation, the model is integrated 41 times starting from a control and 40 perturbed initial conditions. The atmospheric perturbations are identical to those applied to ECMWF medium-range forecasts: singular vectors to perturb the atmospheric initial conditions (Buizza and Palmer 1995) and stochastic perturbations during the model integrations (Buizza et al. 1999, Palmer 2001). For each grid point, the stochastic physics perturbs grid point tendencies up to 50%. The tendencies are multiplied by a random factor drawn from a uniform distribution between 0.5 and 1.5. The random factor is constant within a 10°x10° domain for 6 hours. The whole globe is perturbed. The ocean initial conditions are perturbed by adding small perturbations to SST initial conditions. A set of SST perturbations has been constructed by taking the difference between different SST analyses. For each starting date, 20 combinations of SST perturbations are randomly chosen and applied with a + and - sign, creating 40 perturbed states. A set of wind stress perturbations is also calculated by taking the difference between two monthly wind stress analyses. Nine ocean assimilations (one control and four perturbed) are produced by randomly picking two perturbations from the set of wind stress perturbations and adding them with a + and - sign to the analyzed wind. The wind stress and SST perturbations are combined to produce the 40 perturbed oceanic initial conditions. More details can be found in Anderson et al. (2007).

The forecasts are produced once a month with initial conditions from the 1st of each month. These forecasts are then issued on the 15th of each month (the delay allows acquisition of SST fields from the previous month, time to run the forecasts, and a margin to ensure a reliable operational schedule). A problem with long-term integrations is that the model mean climate begins to be different from the analysis climate. The effect of the drift on the model calculations is estimated from integrations of the model in previous years (the re-forecasts). The drift is removed from the model solution during the post-processing. The re-forecasts consist of an ensemble of 11 members starting on the 1st of each month from 1981 to 2007 (the ECMWF seasonal forecasting system 3 became operational in March 2007).

The tropical storms produced by each forecast are tracked using the method described in Vitart and Stockdale (2001). This method identifies the low pressure systems with a warm core in the upper troposphere from the model outputs every 12 hours. Then an algorithm is applied to build the tropical storm trajectories from the low pressure systems with a warm core which have been identified.

The number of tropical storms for each basin is then counted and added over the 7-month period of model integrations, but the first month of the forecast is excluded since it includes the deterministic part of the forecasts. Also, these forecasts are issued with a delay of 15 days. Since the model components have biases, the climatological frequency of model tropical storms can differ from observations. We calibrate the number of model tropical storms in a given year by multiplying the number of model tropical storms by a factor such that the mean of the central distribution (25%-75% distribution) of the model climate equals the mean of the observed central distribution. The calibration of the re-forecasts is performed using cross-validation.

The ECMWF seasonal forecasts of tropical storms are produced each month for all tropical cyclone basins (e.g., the North Atlantic, the eastern North Pacific, the western North Pacific, the North Indian Ocean, the South Indian Ocean, the Australian basin, and the South Pacific). For instance the seasonal forecasts of tropical storms for the Atlantic basin are issued from March to August. These forecasts do not necessarily cover the full season. For instance the 1st March forecasts, which are issued the 15 March, cover only a portion of the Atlantic tropical storm season: the period from June to September. On the other hand, the forecasts starting on 1st May cover the full Atlantic tropical storm season, from June to November. Four times a year (February, May, August, November), the forecasts are extended to 13 months. The tropical storm forecasts produced by those 13 months forecast are still experimental. Current seasonal tropical storm forecast products at ECMWF include:

- The number of named storms
- The mean genesis location (particularly relevant for the western North Pacific, where the genesis location of tropical storms can vary significantly from year to year)
- The number of hurricanes (product available since May 2008)
- The Accumulated Cyclone Energy (ACE) (product available since May 2008).

The forecasts have been evaluated against observed data. Figure 7.6 shows an example of verification of ACE over the Atlantic for the ECMWF seasonal forecasts starting on 1st June.

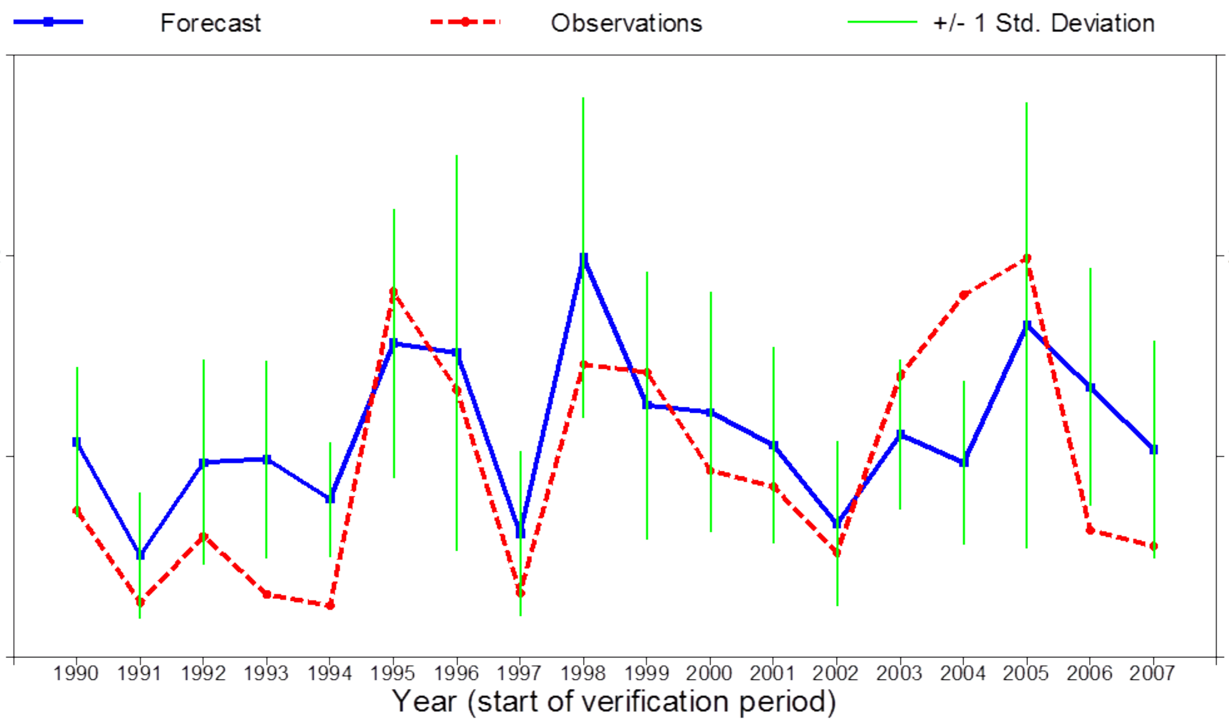


Figure 7.6. Interannual variability of Accumulated Cyclone Energy over the North Atlantic,normalized over its climatological value over the period 1990-2006. The red line represents observations from HURDAT, the blue line represents the interannual variability of the ECMWF ensemble mean forecasts starting on 1st June. The vertical green lines represent 2 standard deviations. The linear correlation between observations and ensemble mean model forecast is 0.72 over the period 1990-1007.

Multi-model prediction

There exist a number of different methods to represent model uncertainty. One method makes use of the so-called multi-model technique. This method consists in combining the forecasts produced by different numerical models. The main idea is that the combination of the different models should filter some of the model error which are specific to one of the model components. The DEMETER project (Palmer et al. 2004) tested this hypothesis by combining the forecasts produced by 7 different coupled ocean-atmosphere seasonal forecasting systems. Vitart (2006) found that the DEMETER multi-model performed better overall than any individual model component. The success of DEMETER, led directly to the development of the operational EUROSIP multi-model ensemble. EUROSIP presently consists of 3 seasonal forecasting systems from the ECMWF, the Met Office and Mé/téo-France. Multi-model seasonal forecasts of tropical storm activity are produced the same way as the ECMWF seasonal forecasts. Each model is calibrated separately and the multi-model tropical storm forecast is the median of the 3 model forecasts. The tropical storm products are the same as for the ECMWF forecast except that we do not issue EUROSIP forecasts of hurricane numbers. This is because some of the model components of EUROSIP do not have enough horizontal resolution to produce hurricanes. As is the case for the ECMWF forecasts, the EUROSIP multi-model tropical storm forecasts are not public, but are available to ECMWF member states. They may soon become available to WMO members. The skill of the EUROSIP multi-model forecasts of tropical storm frequency is discussed in Vitart et al. (2007).

7.7 IRI seasonal hurricane outlooks

Suspect that the IRI experimental hurricane forecasts have been discontinued. We may need to delete all of Section 7.7.

Since 2003, the International Research Institute for Climate and Society (IRI) has been issuing experimental forecasts for seasonal tropical cyclone (TC) activity in different regions based on climate models. The forecasts are issued in the form of tercile probabilities (above-normal, normal, below-normal) for each of the variables (number of tropical cyclones and accumulated cyclone energy) in each basin for the peak of the TC season and are updated monthly. Here we briefly describe how the forecasts are produced and show their hindcast and real time skill in different regions. This manuscript is strongly based on Camargo and Barnston (2008a, b). The figures and tables shown here appeared originally in Camargo and Barnston (2008, 2009).

Description of forecasts

The possible use of dynamical climate models to forecast seasonal TC activity has been explored by various authors, e.g. Bengtsson et al. (1982). Although the typical low horizontal resolution of climate general circulation models is not adequate to realistically reproduce the structure and behavior of individual cyclones, such models are capable of forecasting with some skill several aspects of the general level of TC activity over the course of a season (Camargo et al. 2005). The skill of dynamical TC forecasts depends on many factors, including the model used, the model resolution, and the inherent predictability of the large-scale circulation regimes, including those related to the ENSO condition.

An important consideration is the dynamical design used to produce the forecasts. Currently, there are two methods for producing dynamical TC forecasts. The first is based on fully coupled atmosphere-ocean models (Vitart and Stockdale 2001; Vitart et al. 2007). At IRI a two-tiered procedure is used (Mason et al. 1999; Goddard et al. 2003; Barnston et al. 2003, 2005),in which SST forecast scenarios are first established, which then are used to force an atmospheric model (Camargo and Barnston 2008, 2009).

The atmospheric model used for the IRI TC forecasts is the ECHAM4.5 model, developed at the Max-Planck Institute for Meteorology in Hamburg (Roeckner et al. 1996), which has been studied extensively for various aspects of seasonal TC activity (Camargo and Zebiak 2002; Camargo and Sobel 2004; Camargo et al. 2005, 2007a). The integrations of this atmospheric model are subject to differing SST forcing scenarios, which are in constant improvement at IRI.

Details of current and past SST scenario methodologies are given in Camargo and Barnston (2008, 2009). In the tropics, multi-model SST forecasts are used for the Pacific, while statistical and dynamical forecasts are combined for the Indian and Atlantic Oceans. In all scenarios, the extra-tropical SST forecasts consist of damped persistence from the previous month's observation (added to the forecast season's climatology), with an anomaly e-folding time of 3 months (Mason et al. 1999). The model skill performance was first examined in model simulations forced with observed SSTs, prescribed during the period 1950 to the present. These runs provide estimates of the upper limit of skill model in forecasting TC activity.

For all types of SST we analyze the output of the ECHAM4.5 global climate model for TC activity. To define and track TCs in the models, we used objective algorithms (Camargo and Zebiak 2002), based in large part on prior studies (Vitart et al. 1997; Bengtsson et al. 1995). The algorithm has two parts: detection and tracking. In the detection part, storms that meet environmental and duration criteria are identified. A model TC is identified when chosen dynamical and thermodynamic variables exceed thresholds calibrated to the observed tropical storm climatology. Most studies (Bengtsson et al. 1982, Vitart et al. 1997) use a single set of threshold criteria globally. However, to take into account model biases and deficiencies, we use basin- and model-dependent threshold criteria, based on analyses of the correspondence between the model and observed climatologies. Thus, we use a threshold exclusive to ECHAM4.5 at a specific horizontal resolution.

Once detected, the TC tracks are obtained from the vorticity centroid, defining the center of the TC, using relaxed criteria appropriate for the weak model storms. These detection and tracking algorithms have been applied to regional climate models (Landman et al. 2005; Camargo et al. 2007b) and to multiple AGCMs (Camargo and Zebiak 2002; Camargo et al. 2005, 2007c).

Following detection and tracking, we count the number of named storms (NS) and compute the model accumulated cyclone energy (ACE) index (Bell et al. 2000) over a TC season. ACE is defined as the sum of the squares of the wind speeds in the TCs active in the model at each 6-hour interval. For the observed ACE, only TCs of tropical storm intensity or greater are included. The model ACE and named storm results are then corrected for bias, based on the historical model and observed distributions of NTC and ACE over the 1971-2000 period, on a per-basin basis. Corrections yield matching values in a percentile reference frame (i.e., a correspondence is achieved non-parametrically). Using 1971-2000 as the climatological base period, tercile boundaries for model and observed NTC and ACE are then defined, since the forecasts are probabilistic with respect to tercile-based categories of the climatology (below, near, and above normal).

For each of the SST forcing designs, we count the number of ensemble members having their named storms and ACE in a given ocean basin in the below-normal, normal and above-normal categories, and divide by the total number of ensembles. These constitute the "raw", objective probability forecasts. In a final stage of forecast production,the IRI forecasters examine and discuss these objective forecasts and develop subjective final forecasts that are issued on the IRI website. The most typical difference between the raw and the subjective forecasts is that the latter have weaker probabilistic deviations from climatology, given the knowledge that the models are usually too "confident". The overconfidence of the model may be associated with too narrow an ensemble spread, too strong a model signal (deviation of ensemble mean from climatology), or both of these. The subjective modification is intended to increase the probabilistic reliability of the predictions. Another consideration in the subjective modification is the degree of agreement among the forecasts, in which less agreement would suggest greater uncertainty and thus more caution with respect to the amount of deviation from the climatological probabilities.

The raw objective forecasts are available since August 2001. The first subjective forecast for the western North Pacific basin was produced in real-time in April 2003. However, subjective hindcasts were also produced for August 2001 through April 2003 without knowledge of the observed result, making for 6 years of experimental forecasts.

For each ocean basin, forecasts are produced only for the peak TC season, from certain initial months prior to that season (Table 7.9), and updated monthly until the first month of the peak season. The lead time of this latest forecast is defined as being zero, and the lead times of earlier forecasts are defined by the number of months earlier that they are issued. The definitions of the basins' boundaries are given in Fig. 7.7.

Table 7.9. Ocean basins in which IRI experimental TC forecasts are issued: Eastern North Pacific (ENP), Western North Pacific (WNP), North Atlantic (ATL), Australia (AUS) and South Pacific (SP). Date of the first issued forecast; seasons for which TC forecasts are issued (JJAS: June to September, ASO: August-October, JASO: July to October, ASO: August to October, JFM: January to March, DJFM: December to March); months in which the forecasts are issued; and variables forecasted—NS (named storms), ACE (accumulated cyclone energy).

Basin	First Forecast	Season	Months forecasts are issued	Variables
Eastern North Pacific (ENP)	March 2004	JJAS	Mar, Apr, May, Jun	NS,ACE
Western North Pacific (WNP)	April 2003	JASO	Apr, May, Jun, Jul	NS,ACE
North Atlantic (ATL)	June 2003	ASO	Apr, May, Jun, Jul, Aug	NS,ACE
Australia (AUS)	September 2003	JFM	Sep, Oct, Nov, Dec, Jan	NTC
South Pacific (SP)	September 2003	DJFM	Sep, Oct, Nov, Dec	NTC

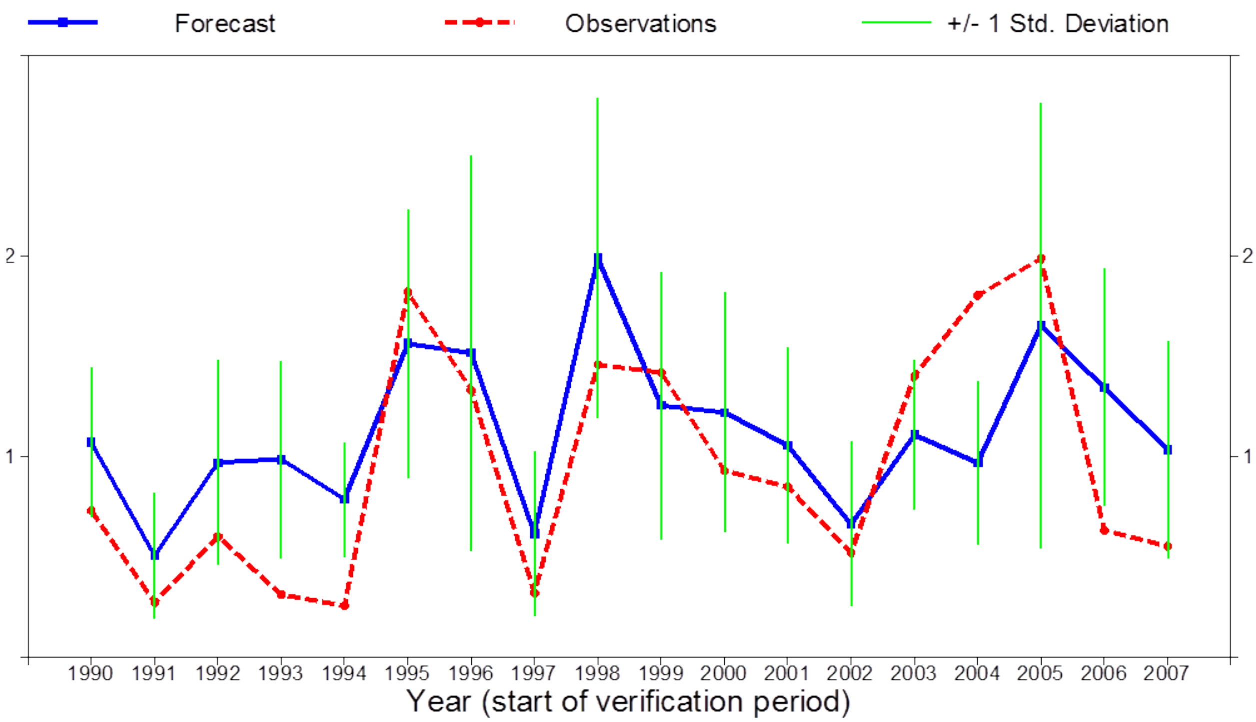


Figure 7.7. Definition of the ocean basin domains used in this study: Australian (AUS),(105°E-165°E); South Pacific(SP), 165°E-110°W; western North Pacific (WNP), 100°E-160°W, eastern North Pacific (ENP), 160°W-100°W; and Atlantic (ATL), 100°W-0°. All latitude boundaries are along the equator and 40°N or 40°S. Note the unique boundary paralleling Central America for ENP and ATL basins.

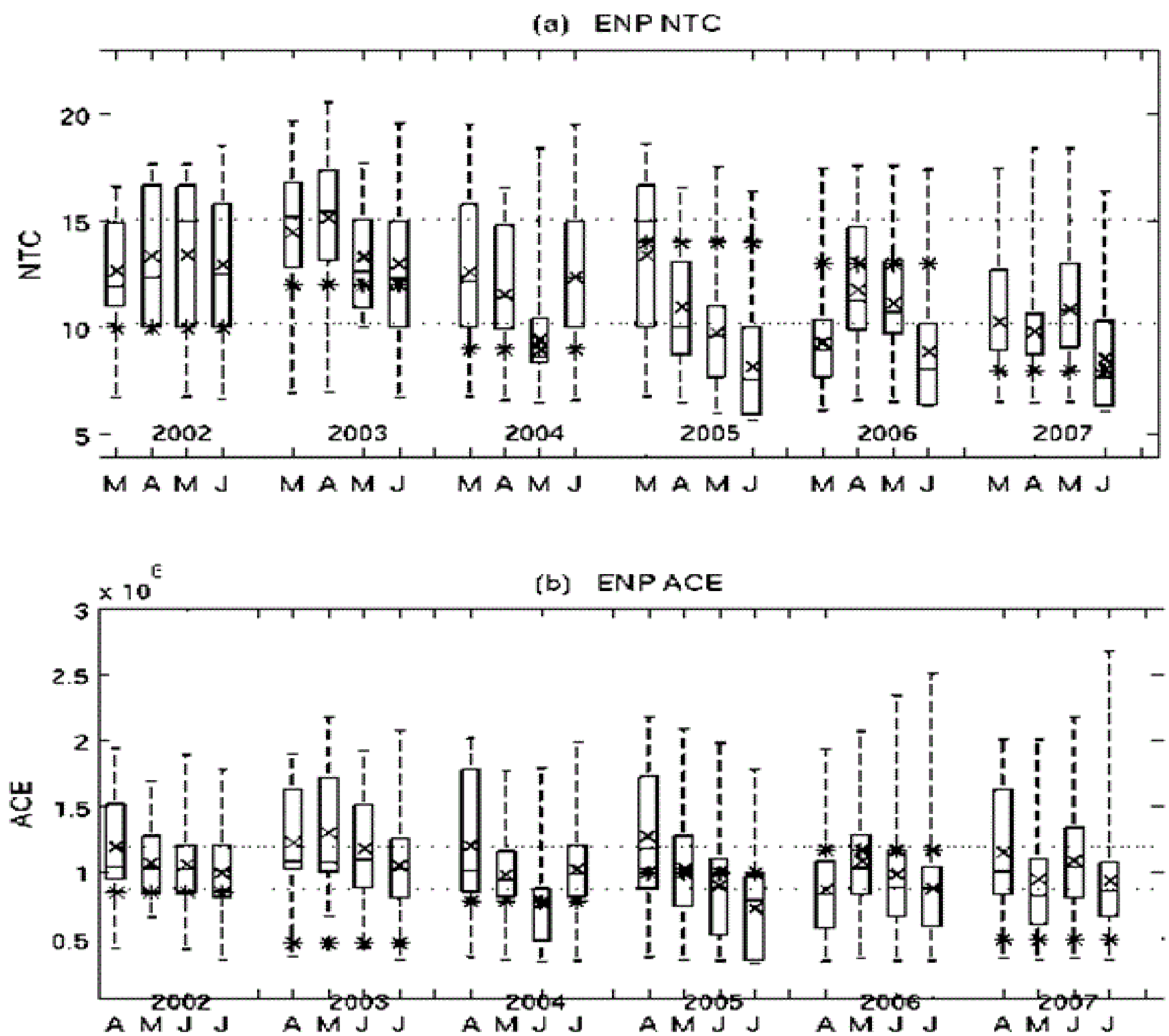
Forecasts and hindcast skill

In Camargo and Barnston (2008, 2009), a large set of probabilistic and deterministic skill score measures are examined for simulations (forced with observed SST), hindcasts of persisted SSTs and the real-time forecasts.Here we show just a subset of that skill analysis.

Figure 7.8 shows the approximate 6-year record of the model ensemble forecasts of NTC and ACE at all forecast lead times for each of the ocean basins. The vertical boxes show the inter-quartile range among the ensemble members,and the vertical dashed lines ("whiskers") extend to the ensemble member forecasts outside of that range. The asterisk indicates the observation value. Favorable and unfavorable forecast outcomes can be identified, such as, respectively, the ACE forecasts for the western North Pacific for 2002, and the ACE forecasts for the North Atlantic for 2004.

Probabilistic verification using the ranked probability skill score (RPSS) and likelihood scores for NTC and ACE, using the multi-decadal simulations and hindcasts (OSST and HSST), and the real-time forecasts forced by the multiple SST prediction scenarios lead to skills that are mainly near or below zero. This poor result can be attributed to the lack of probabilistic reliability of atmospheric ensemble-based TC predictions as is seen in many predictions made by individual climate models — not just for TC activity but for most climate variables (Anderson 1996; Barnston et al. 2003; Wilks 2006). Climate predictions by atmospheric models have model-specific systematic biases, and their uncorrected probabilities tend to deviate too strongly from climatological probabilities due to too small an ensemble spread and/or too large a mean shift from climatology. This problem leads to comparably poor probability forecasts, despite positive correlation skills for the ensemble means of the same forecast sets. Positive correlations, but negative probabilistic verification is symptomatic of poorly calibrated probability forecasts — a condition that can be remedied using objective statistical correction procedures.

The actually issued forecasts have better probabilistic reliability than the forecasts of the model output. Likelihood skill scores,and especially RPSS, are mainly positive for the issued forecasts, although modest in magnitude. This implies that the probability forecasts of the atmospheric are potentially useful, once calibrated to correct for overconfidence or an implausible distribution shape. Such calibration could be done objectively, based on the longer hindcast history, rather than subjectively by the forecasters as done to first order here.



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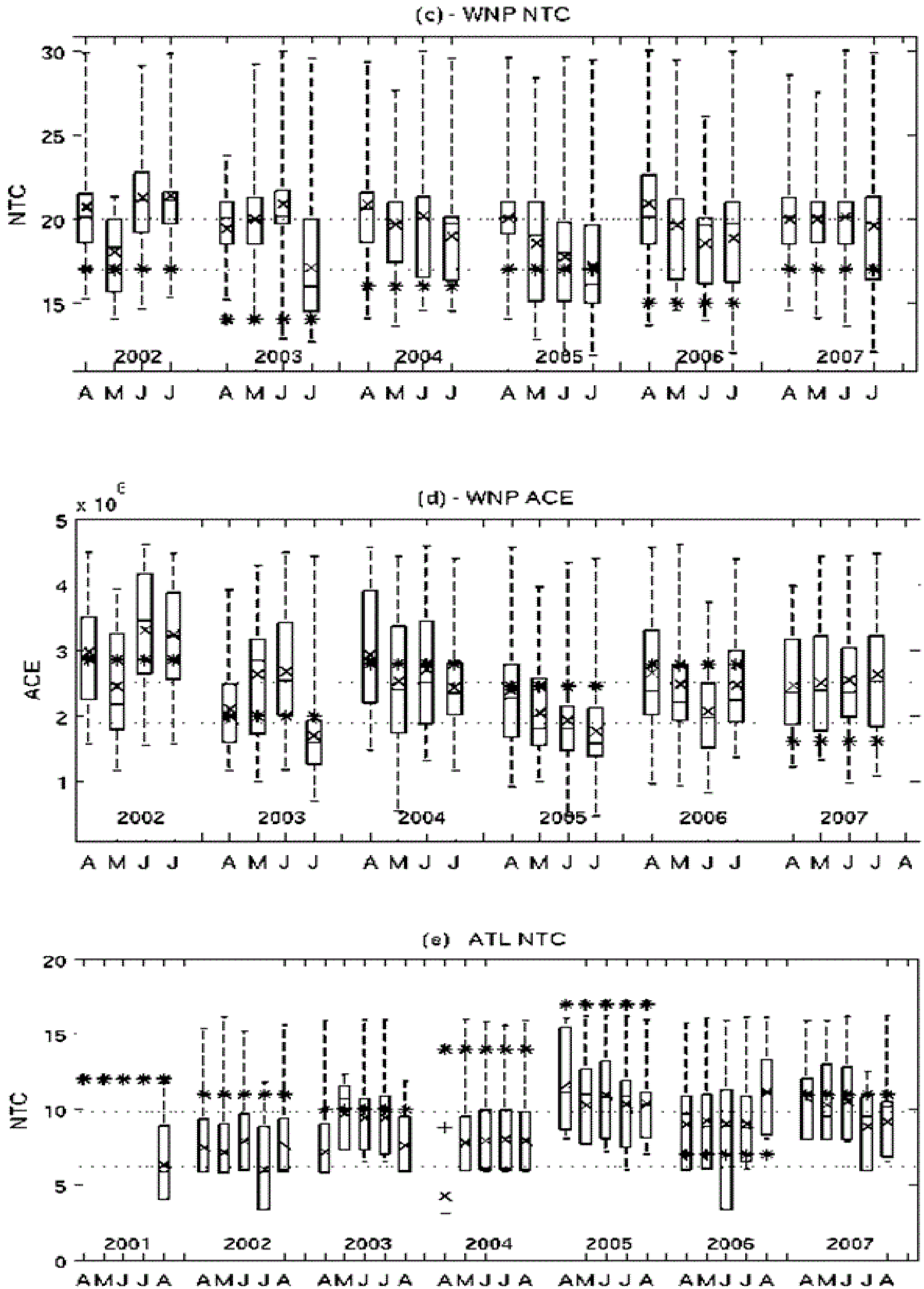

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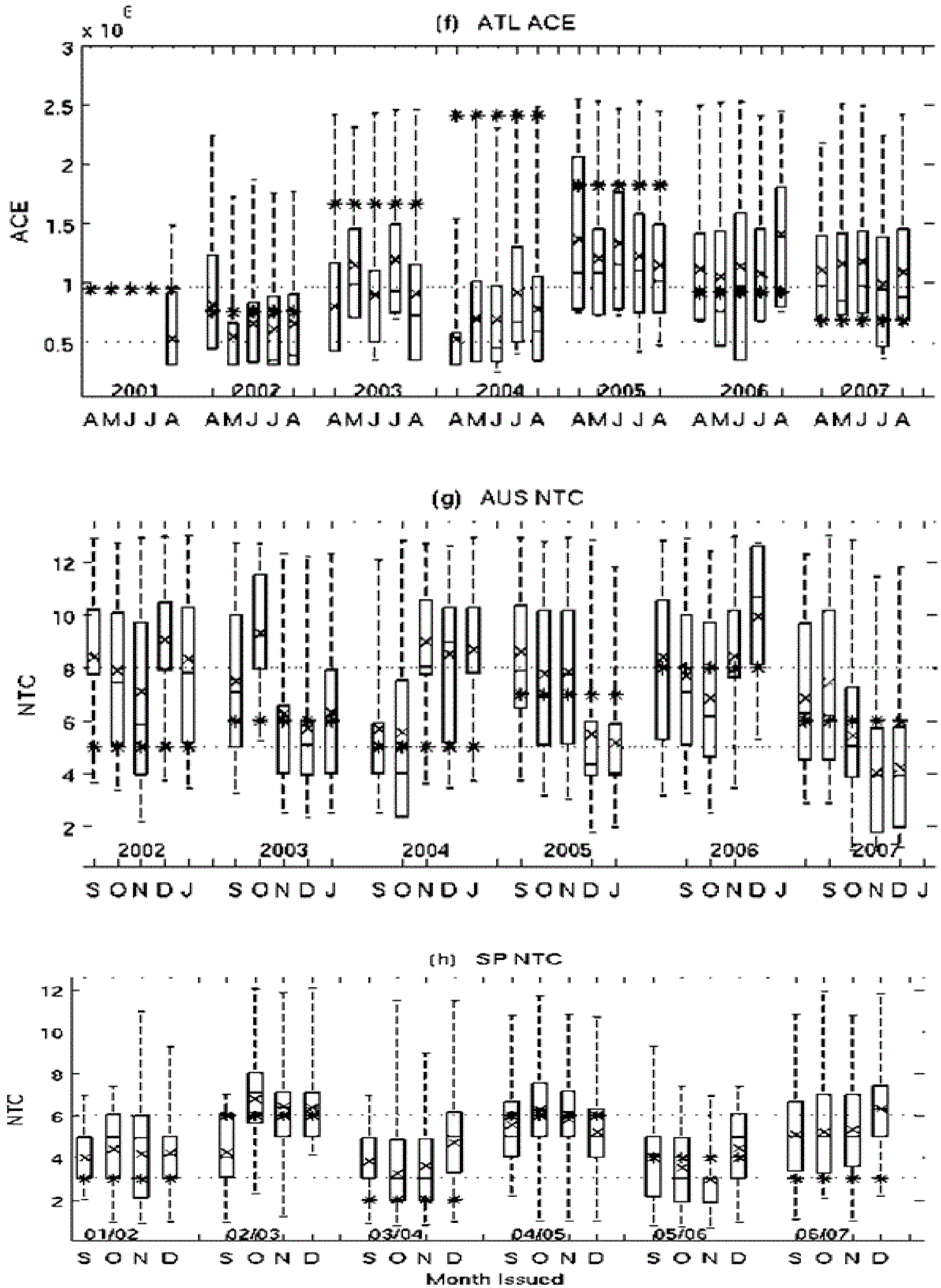

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Figure 7.8. Model (raw)forecasts (box plots and whiskers)and observations (asterisks)of number of TCs (NTC)and accumulated cyclone energy (ACE)for all basins and leads. The cross inside the box shows the ensemble mean, and the horizontal line shows the median. Also shown by dotted horizontal lines are the boundaries between the tercile categories. Panels(a)-(f) are for the northern hemisphere basins, with NTC on the left panels and ACE on right panels, for ENP, ATL,W NP in each row, respectively. The two bottom panels are for NTC in the southern hemisphere basins: AUS (g) and SP (h).

7.8 Summary

The International Research Institute for Climate and Society (IRI) has been issuing experimental TC activity forecasts for several ocean basins since early 2003. The forecasts are based on TC-like features detected and tracked in the ECHAM4.5 atmospheric model, at low horizontal resolution (T42). The model is forced at its lower boundary by sea surface temperatures (SSTs) that are predicted first, using several other dynamical and statistical models. Results show that low-resolution model deliver statistically significant, but fairly modest, skill in predicting the inter-annual variability of TC activity. In a 2-tiered dynamical prediction system such as that used in the IRI forecasts, the effect of imperfect SST prediction is noticeable in skills of TC activity compared with skills when the model is forced with historically observed SSTs.

Although prospects for the future improvement of dynamical TC prediction are uncertain,it appears likely that additional improvements in dynamical systems will make possible better TC predictions. As is the case for dynamical approaches to ENSO and near-surface climate prediction, future improvements will depend on better understanding of the underlying physics,more direct physical representation through higher spatial resolution, and substantial increases in computer capacity. Hence, improved TC prediction should be a natural by-product of improved prediction of ENSO, global tropical SST, and climate across various spatial scales.

7.9 Reference

Anderson, J.L., 1996: A method for producing and evaluating probabilistic forecasts from ensemble model integrations. *J. Climate*, **9**, 1518-1530.

Anderson, D., T. Stockdale, M. Balmaseda, L. Ferranti, F. Vitart, F. Molteni, F. Doblas-Reyes, K. Mogensen and A. Vidard, 2007: Development of the ECMWF seasonal forecast system 3, ECMWF Tech. Memo., 503.

Balmaseda, M., A. Vidard and D. Anderson, 2007: The ECMWF system 3 ocean analysis, ECMWF Tech. Memo., 508.

Barnston, A.G., A. Kumar, L. Goddard, and M. P. Hoerling, 2005: Improving seasonal prediction practices through attribution of climate variability. *Bull. Amer. Meteor. Soc.*, **86**, 59-72.

Barnston, A.G., S.J. Mason, L. Goddard, D.G. DeWitt, and S.E. Zebiak, 2003: Multimodel ensembling in seasonal climate forecasting at IRI. *Bull. Amer. Meteor. Soc.*, **84**, 1783-1796.

Bell, G. D., and M. Chelliah, 2006: Leading tropical modes associated with interannual and multi-decadal fluctuations in North Atlantic hurricane activity. *J. Climate*. **19**, 590-612.

Bell, G. D., et al., 2000: Climate assessment for 1999. *Bull. Amer. Meteor. Soc.*, **81**, S1-S50.

Bengtsson, L., H. Böttger, and M. Kanamitsu, 1982: Simulation of hurricane-type vortices in a general circulation model. *Tellus*, **34**, 440-457.

Bengtsson, L., M. Botzet, and M. Esch, 1995: Hurricane-type vortices in a general circulation model. *Tellus* **47A**: 175-196

Buizza, R. and T. Palmer, 1995: The singular-vector structure of the atmospheric global circulation. *J. Atmos. Sci.*, **52**, 1434-2456.

Buizza, R., M. Millter, and T.N. Palmer, 1999: Stochastic representation of model uncertainties in the ECMWF ensemble prediction system. Quart. *J. Roy. Meteor. Soc.*, **125**, 1887-2908.

Camargo, S. J., and A. G. Barnston, 2009: Experimental seasonal dynamical forecasts of tropical cyclone activity at IRI. *Wea. Forecasting*, **24**, 472–491

Camargo, S. J., and A. G. Barnston, 2008: Description and skill evaluation of experimental dynamical seasonal forecasts of tropical cyclone activity at IRI, *IRI Technical Report 08-02*, International Research Institute for Climate and Society, Columbia University, Palisades, NY.

Camargo, S. J., and A. H. Sobel, 2004: Formation of tropical storms in an atmospheric general circulation model. *Tellus*, **56A**, 56-67.

Camargo, S. J., and S. E. Zebiak, 2002: Improving the detection and tracking of tropical cyclones in atmospheric general circulation models. *Wea. Forecasting*, **17**, 1152-1162.

Camargo, S. J., A. G. Barnston, and S. E. Zebiak, 2005: A statistical assessment of tropical cyclone activity in atmospheric general circulation models. *Tellus*, **57A**: 589-604.

Camargo, S.J., A.G. Barnston, P.J. Klotzbach, and C.W. Landsea, 2007a: Seasonal tropical cyclone forecasts. *Bulletin of the World Meteorological Organization*, **56**, 297-307

Camargo, S. J., H. Li, L. Sun, 2007b: Feasibility study for downscaling seasonal tropical cyclone activity using the NCEP regional spectral model. Int. *J. Climate*, **27**, 311-325.

Camargo, S. J., A. H. Sobel, A. G. Barnston, and K. A. Emanuel, 2007c: Tropical cyclone genesis potential index in climate models. *Tellus*, **59A**, 428-443.

Chen, T.C., Yoon, J., Croix, K.J., and Takle, E.S., 2001: Suppressing impacts of Amazonian deforestation by global circulation change. *Bull. Amer. Meteorol. Soc.* **82** 2209-2215.

Chu, P.S., Z.P. Yu, and S. Hastenrath, 1994: Detecting climate change concurrent with deforestation in the Amazon Basin: Which way has it gone? *Bull. Amer. Meteorol. Soc.* **75** 579-583.

Ebisuzaki, W., M. Chelliah, and R. Kistler, 1996: NCEP/NCAR Reanalysis: Caveats. In Proc. First WMO Reanalysis Workshop, Silver Spring, MD.

Efron, B. and G. Gong, 1983: A leisurely look at the bootstrap, the jackknife, and cross-validation. *The American Statistician*, **37**, 36-48.

Goddard, L., A.G. Barnston, and S.J. Mason, 2003: Evaluation of the IRI's "Net Assessment" seasonal climate forecasts: 1997-2001. *Bull. Amer. Meteor. Soc*., **84**, 1761-1781.

Goldenberg, S. B., and L. J. Shapiro, 1996: Physical mechanisms for the association of El Niño and West African rainfall with Atlantic major hurricane activity. *J. Climate*, **9** 1169-1187.

Gray, W. M., 1990: Strong association between West African rainfall and U.S. landfall of intense hurricanes. *Science*, **249**, 1251-1256.

Gray, W. M., J. D. Sheaffer, and C. W. Landsea, 1996: Climate Trends associated with multi-decadal variability of Atlantic hurricane activity.*Hurricanes: Climate and Socioeconomic Impacts*. H. E. Diaz and R. S. Pulwarty, eds., Springer-Verlag, 292 pp.

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

Gray, W. M., 1984b: Atlantic seasonal hurricane frequency. Part II: Forecasting its variability. *Mon. Wea. Rev.*, **112**, 1669-1683.

Gray, W. M., C. W. Landsea, P. W. Mielke Jr., and K. J. Berry, 1992: Predicting Atlantic seasonal hurricane activity 6-11 months in advance. *Wea. Forecasting*, **7**, 440-455.

Gray, W. M., C. W. Landsea, P. W. Mielke Jr., and K. J. Berry, 1994: Predicting Atlantic basin seasonal tropical cyclone activity by 1 June. *Wea. Forecasting*, **9**, 103-115.

Hastenrath, S., 1990: Decadal-scale changes of the circulation in the tropical Atlantic sector associated with Sahel drought. Int. *J. Climatol*., **10**, 459-472.

Kalnay, E., and Co-authors, 1996: The NCEP/NCAR 4-year Reanalysis project. *Bull. Amer. Meteor. Soc.,* **77,** 437-471.

Kistler, R., and Co-authors, 2001: The NCEP/NCAR 50 year reanalysis: Monthly means CD-ROM and documentation. *Bull. Amer. Meteor. Soc.*, **82**, 247-268

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

Klotzbach, P. J., 2008: Refinements to Atlantic basin seasonal hurricane prediction from 1 December. *J. Geophys. Res.*, **113**, D17109, doi:10.1029/2008JD010047.

Klotzbach, P. J., and W. M. Gray, 2004: Updated 6-11 month prediction of Atlantic basin seasonal hurricane activity. *Wea. Forecasting*, **19**, 917-934.

Klotzbach, P. J., and W. M. Gray, 2008a: Extended range forecast of Atlantic seasonal hurricane activity and U.S. landfall strike probability for 2008. Dept. of Atmospheric Science Rep., Colorado State University, Fort Collins, CO, 32 pp.

Klotzbach, P. J., and W. M. Gray, 2008b: Extended range forecast of Atlantic seasonal hurricane activity and U.S. landfall strike probability for 2008. (updated). Dept. of Atmospheric Science Rep., Colorado State University, Fort Collins, CO, 39 pp.

Landman, W. A., A. Seth, and S. J. Camargo, 2005: The effect of regional climate model domain choice on the simulation of tropical cyclone-like vortices in the Southwestern Indian Ocean. *J. Climate*, **18**, 1253-1274.

Landsea, C. W., and W. M. Gray, 1992: The strong association between Western Sahel monsoon rainfall and intense Atlantic hurricanes. *J. Climate*, **5**, 435-453.

Landsea, C. W., W. M. Gray, P. W. Mielke, and K. J. Berry, 1992: Long-term variations of western Sahelian monsoon rainfall and intense U.S. landfalling hurricanes. *J. Climate*, **5**, 1528-1534.

Landsea, C. W., R. A. Pielke, Jr., and A. M. Mestas-Nuñez, 1999: Atlantic basin hurricanes: Indices of climate change. *Climate Change*, **42**, 89-129.

Lea, A. S., and M. A. Saunders, 2004: Seasonal predictability of Accumulated Cyclone Energy in the North Atlantic, Proceedings of the 26th Conference on Hurricanes and Tropical Meteorology, Miami, USA, May 3-7, pp. 419-420.

Lea, A. S. and M. A. Saunders, 2006a: Seasonal prediction of typhoon activity in the Northwest Pacific basin, *27th Conference on Hurricanes and Tropical Meteorology*, Monterey, CA, USA, April 24-28 (poster paper).

Lea, A. S. and M. A. Saunders, 2006b: How well forecast were the 2004 and 2005 Atlantic and US hurricane seasons? *Weather*, **61**, 245-249.

Lloyd-Hughes, B., M. A. Saunders and P. Rockett, 2004: A consolidated CLIPER model for improved August-September ENSO prediction skill, *Wea Forecasting*, **19,** 1089-1105.

Mason, S.J., L. Goddard, N.E. Graham, E. Yulaeva, L.Q. Sun, and P.A. Arkin,1999: The IRI seasonal climate prediction system and the 1997/98 El Niño event. *Bull. Amer. Meteor. Soc.*, **80**, 1853-187.

Palmer, T.N., and coauthors, 2004: Development of a European Multimodel Ensemble System for seasonal to interannual prediction (DEMETER), *Bull. Amer. Meteor. Soc.*, **85**, 853-872.

Palmer, T., 2001: A nonlinear dynamic perspective on model error: A proposal for nonlocal stochastic dynamic parametrization in weather and climate prediction systems. *Quart. J. Roy. Meteor. Soc.*, **127**, 279-304.

Roeckner, E., et al., 1996: The atmospheric general circulation model ECHAM-4: Model description and simulation of present-day climate. Tech. Rep. 218, Max-Planck Institute for Meteorology, Hamburg, Germany. 90 pp.

Saunders, M. A., 2006: Winds of change. *Post Magazine Risk Report*, pp. 28-29, 9 November 2006.

Saunders, M. A. and A. S. Lea, 2005: Seasonal prediction of hurricane activity reaching the coast of the United States. *Nature*, **434**, 1005-1008.

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.

Vitart, F., 2006: Seasonal forecasting of tropical storm frequency using a multi-model ensemble. *Quart. J. Roy. Meteor. Soc.*, **132,** 647-666.

Vitart, F., J. L. Anderson, and W. F. Stern, 1997: Simulation of interannual variability of tropical storm frequency in an ensemble of GCM integrations. *J. Climate*, **10**, 745-760.

Vitart, F., M.R. Huddleston, M. Déqué, D. Peake, T.N. Palmer, T.N. Stockdale, M.K. Davey, S. Inenson, 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.

Vitart F. D. and T. N. Stockdale, 2001: Seasonal forecasting of tropical storms using coupled GCM integrations. *Mon. Wea. Rev.*, **129**, 2521-2537.

Wilks, D. S., 2006: Statistical Methods in the Atmospheric Sciences, 2nd Ed. *International Geophysics Series,* **Vol. 59**, Academic Press, 627 pp.