



Seasonal tropical cyclone forecasts

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Introduction

Seasonal forecasts of tropical cyclone activity in various regions have been developed since the first attempts in the early 1980s by Neville Nicholls (1979) for the Australian region and William Gray (1984(a), (b)) for the North Atlantic region. Over time, forecasts for different regions, using differing methodologies, have been developed. Tourism in various regions, such as the US Gulf and East Coasts and the Caribbean, is impacted by these seasonal forecasts. Insurance and re-insurance companies also make use of seasonal forecasts in their policy decisions. It is fundamental to provide these users with information about the accuracy of seasonal forecasts. Seasonal forecasts have limited use for emergency managers, because of the lack of skill in predicting impacts at the city or county level.

As has been the case in some of the previous WMO International Workshops on Tropical Cyclones (ITWC), a review of the progress on seasonal forecasts of tropical cyclone activity was presented at the IWTC-VI in San José, Costa Rica, in November 2006 (Camargo

Statistical and dynamical seasonal tropical cyclone activity forecasts are proposed to be made available on a public Website for forecasters and other users.

et al., 2006). These quadrennial workshops, co-sponsored by the WMO Commission for Atmospheric Science Tropical Meteorology Research Programme and the World Weather Watch Tropical Cyclone Programme, bring together tropical cyclone forecasters and researchers to review progress and plan for future activities in topics such as seasonal forecasts. During IWTC-VI, forecasters from various countries shared information about seasonal tropical cyclone forecasts currently being issued by their respective countries—which was often information not well known by other scientists present.

Forecasters in National Meteorological and Hydrological Services are interested in seasonal forecasts because they are frequently asked questions by the media and various decision-makers. Interest from the media and the general public in

seasonal tropical cyclone forecasts has increased tremendously since they were first produced, especially after 2004, when 10 tropical cyclones struck Japan and four hurricanes impacted Florida, USA.

Although landfall forecasts are particularly important to users, landfall forecast skill is still limited. As seasonal tropical cyclone forecasts improve, more attention will be given to particular details such as regional landfall probabilities. The use of such specific forecasts will become more widespread and significant to decision-makers and residents in coastal areas.

With the popularization of these forecasts, it is fundamental that their documentation and verification become widely available. It is recommended that WMO develop guidelines for the development and validation of these forecasts, similar to the protocol that has been developed for global seasonal climate (temperature and precipitation) forecasts (WMO, 2001). A summary of groups that issue tropical cyclone seasonal forecasts is given in Table I.

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Table 1 — Seasonal tropical cyclone forecasts: groups that issue the forecasts, regions in which the forecasts are issued, forecast type, Website where the forecast is available.

<i>Group</i>	<i>Basins</i>	<i>Type</i>	<i>Website</i>
City University of Hong Kong, China (CityU)	Western North Pacific	Statistical	http://aposf02.cityu.edu.hk
Colorado State University, USA (CSU)	Atlantic	Statistical	http://hurricane.atmos.colostate.edu
Cuban Meteorological Institute (INSMET)	Atlantic	Statistical	http://www.met.inf.cu
European Centre for Medium-Range Weather Forecasts (ECMWF)	Atlantic Austrian Eastern North Pacific North Indian South Indian South Pacific Western North Pacific	Dynamical	http://www.ecmwf.int (collaborating agencies only)
International Research Institute for Climate and Society (IRI)	Atlantic Australia Eastern North Pacific South Pacific Western North Pacific	Dynamical	http://iri.columbia.edu/forecast/tc_fcst/
Macquarie University, Australia	Australia / southwest Pacific	Statistical	http://www.iges.org/ellfb/past.html
Meteorological Office, United Kingdom (MetOffice)	North Atlantic	Dynamical	http://www.metoffice.gov.uk/weather/tropicalcyclone/northatlantic
National Meteorological Service, Mexico (NSM)	Eastern North Pacific	Statistical	http://smn.cna.gob.mx
National Climate Centre, China	Western North Pacific	Statistical	http://bcc.cma.gov.cn
NOAA hurricane outlooks	Atlantic Eastern North Pacific Central North Pacific	Statistical	http://www.cpc.noaa.gov http://www.cpc.noaa.gov http://www.prh.noaa.gov/hnl/cphc
Tropical Storm Risk (TSR)	Atlantic Western North Pacific Australian region	Statistical	http://tsr.mssl.ucl.ac.uk

Statistical seasonal hurricane forecasts

Colorado State University

Initial seasonal predictions for the North Atlantic basin (Gray, 1984(a), (b)) were issued by Colorado State University in early June and early August, beginning in 1984, using statistical relationships between tropical cyclone activity and El Niño/Southern Oscillation (ENSO), the Quasi-Biennial Oscillation (QBO) and Caribbean basin sea-level pressures. Comparatively, more tropical cyclones were predicted in the cool phase

of ENSO, when the QBO was in its west phase and Caribbean basin sea-level pressures were below normal. Statistical forecast techniques for North Atlantic tropical cyclones have evolved since these early forecasts. Additional predictors were added to the original forecast scheme, the QBO is not used as a predictor anymore and the seasonal forecasts started being issued in early December of the previous year. Klotzbach and Gray (2004) and Klotzbach (2007) explain the current forecast scheme.

Owens and Landsea (2003) examined the skill of Gray's operational

Atlantic seasonal tropical cyclone forecasts relative to climatology and persistence. Their analysis indicated that for the analysed period (1984–2001), both the basic statistical forecasts and an adjusted version demonstrated skill over climatology and persistence, with the adjusted forecasts being more skilful than the basic forecasts.

Figure 1 shows the skill of the CSU forecasts for various leads, using linear correlation as a skill measure. The skill improves tremendously in June and August, probably because the ENSO spring barrier is over. Since the ENSO

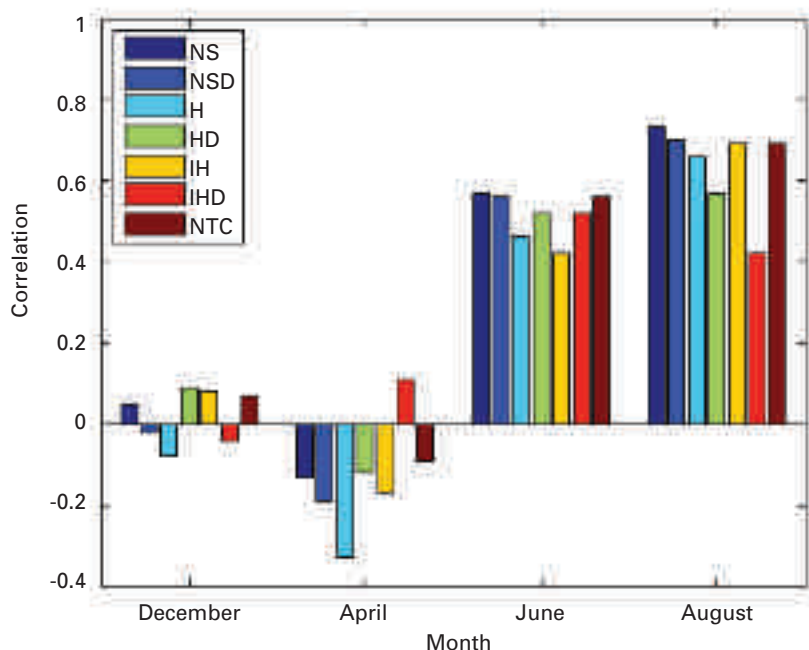


Figure 1 — Correlations of the CSU seasonal forecasts for different leads: December (1992–2006), April (1995–2006), June (1984–2006 or 1990–2006) and August (1984–2006 or 1990–2006). The correlations are given for: number of named storms (NS), number of named storm days (NSD), number of hurricanes (H), number of hurricane days (HD), number of intense hurricanes (IH), number of intense hurricane days (IHD) and net tropical cyclone activity (NTC). Significant correlations at the 95% significance level are: June – NS, NSD, H, HD, IH, IHD, NTC, August – NS, NSD, H, HD, IH and NTC. None of the correlations is significant for the December and April leads.

state is usually defined by June, the hurricane forecasts made in June or later become more skilful. Another reason for a higher skill in June and August is that the season is about to start or has already started.

CSU started issuing forecasts of landfall probabilities in August 1998. The landfall probabilities are based upon a forecast of net tropical cyclone activity. In general, when an active season is predicted (high net tropical cyclone activity), the probability of landfall is increased (Klotzbach, 2007).

National Oceanic and Atmospheric Administration (NOAA)

NOAA has been issuing seasonal hurricane outlooks for the Atlantic and the eastern North Pacific regions since 1998 and 2003, respectively. These outlooks are provided to the public

as deterministic and probabilistic, using terciles. They are based on the state of ENSO (Gray, 1984(a)) and the tropical multi-decadal mode (e.g. Chelliah and Bell, 2004), which incorporates the leading modes of tropical convective rainfall variability occurring on multi-decadal time scales. Important aspects of this signal that are related to an active Atlantic hurricane season include a strong West African monsoon, reduced vertical wind shear in the tropical Atlantic, suppressed convection in the Amazon basin and high tropical Atlantic sea-surface temperatures (SSTs) (Goldenberg *et al.*, 2001). The NOAA forecasts and verifications for named storms, hurricanes, major hurricanes and accumulated cyclone energy (ACE) (Bell *et al.*, 2000) over the period from 1998–2006 are given in Figure 2.

Since 1997, the Central Pacific Hurricane Center issues in May seasonal forecasts for the range of

the number of tropical cyclones in the Central North Pacific region based on the ENSO state and the Pacific decadal oscillation.

Tropical Storm Risk (TSR)

Tropical Storm Risk issues statistical forecasts for tropical cyclone activity in the Atlantic, western North Pacific and Australian regions. The seasonal prediction model uses ENSO forecasts (Lloyd-Hughes *et al.*, 2004) to predict the western North Pacific ACE index and is skilful in hindcast mode in that region (Lea and Saunders, 2006).

In a recent paper (Saunders and Lea, 2005), TSR describes its new forecast model, issued in early August, for seasonal predictions of hurricane landfall activity for the US coastline. The model uses July wind patterns to predict the seasonal US ACE index (effectively, the cumulative wind energy from all tropical cyclones which strike the USA). The July height-averaged winds in these regions are indicative of atmospheric circulation patterns that either favour or hinder hurricanes from reaching US shores. The model correctly anticipates whether US hurricane losses are above- or below-median in 74 per cent of the hindcasts for the 1950–2003 period. The model also performed well in “real-time” operation in 2004 and 2005, while over-predicting in 2006.

City University of Hong Kong, China

Johnny Chan and colleagues have issued seasonal tropical cyclone forecasts for the North-west Pacific basin (number of tropical cyclones and typhoons) since 1997. The statistical predictions are based on various environmental conditions in the prior year, up to the northern hemisphere spring of the forecast season. The most prominent atmospheric and oceanic conditions include ENSO, the extent of the Pacific subtropical ridge and the intensity of the India-

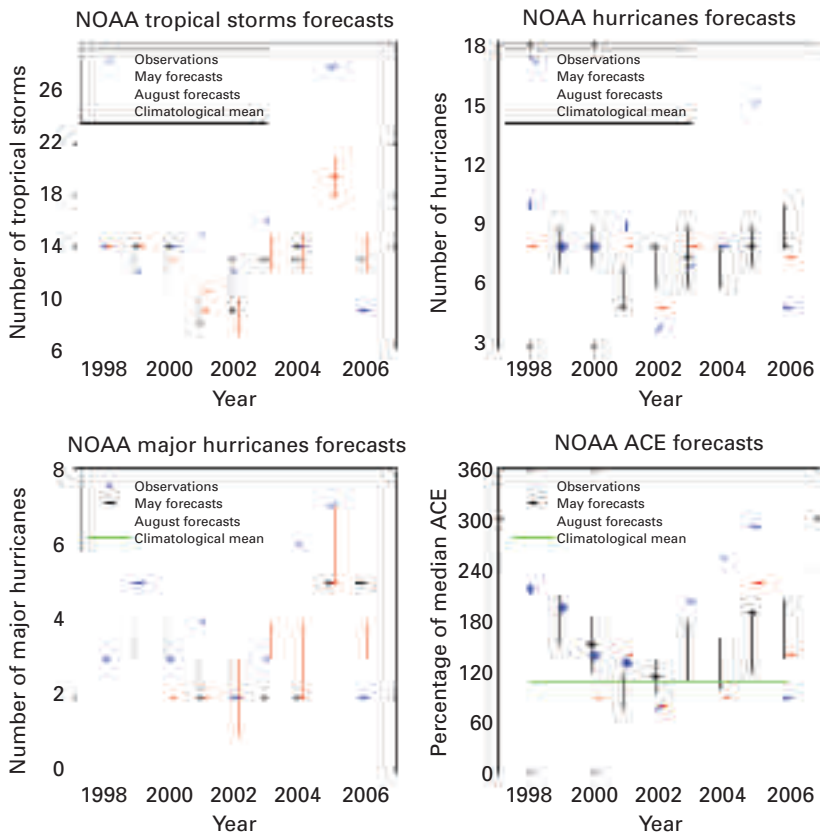


Figure 2 — NOAA forecasts (May and August leads) and observations for tropical cyclones with tropical storm intensity or higher, hurricanes, major hurricanes and ACE (Accumulated Cyclone Energy, Bell et al., 2000) for the period 1998-2006

Burma trough (Chan et al., 1998). For a few years, forecasts of the number of tropical cyclones making landfall were also issued (Liu and Chan, 2003). Currently, the landfall forecast scheme for the South China Sea is being improved. The City University of Hong Kong, China, forecasts and the verifications are shown in Figure 3. In most years, the observed number of tropical cyclones is within the range of the forecast number of tropical cyclones, with the exception of 2006.

Cuban Meteorological Institute

The Cuban Meteorological Institute has been issuing seasonal forecasts of Atlantic hurricane activity since 1996. Currently, the Cuban seasonal forecast is based on the solution of a regression and an analogue method and predicts various tropical cyclone

parameters (see Table II) (Ballester et al., 2004(a) and (b)). The Cuban Meteorological Institute also issues statistical landfall forecasts for Cuba based on a discriminant function methodology (Davis, 1986).

Florida State University (FSU)

James Elsner and colleagues have been developing techniques for modelling seasonal hurricane activity and landfall. Although their forecasts are not produced operationally, their methodology is currently used to issue region-specific forecasts for various companies (James Elsner, personal communication, 2006). The FSU group pioneered various topics in seasonal forecasting, such as the use of a Poisson distribution for hurricane counts (Elsner and Schmertmann, 1993), the influence of the phase of the North Atlantic Oscillation on Atlantic hurricane tracks and US coastal hurricane activity (Elsner et al., 2001), and the development of a skilful statistical model for seasonal forecasts of landfall probability over

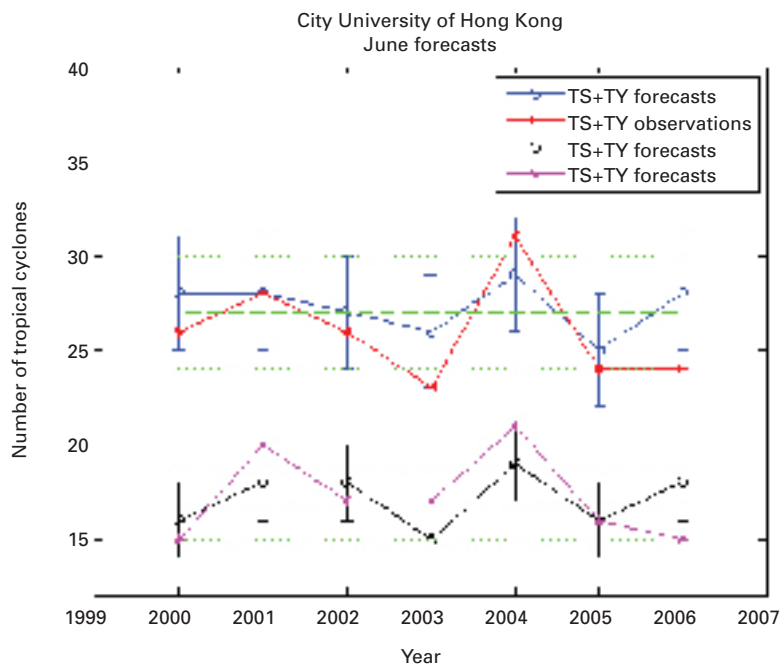


Figure 3 — Verification of the City University of Hong Kong, China, forecasts issued in early June: (top) the number of tropical storms and typhoons (TS+TY) observed and forecast range; (bottom) the number of typhoons (TY) observed and forecast range. In green are the mean climatological number and the corresponding climatological standard deviation.

Table II — Seasonal tropical cyclone forecasts: predictors and outputs used for each group. The group acronyms are defined in Table I. Other acronyms: TCs (tropical cyclones), ENSO (El Niño-Southern Oscillation), SST (sea-surface temperature), SLP (sea-level pressure), SOI (Southern Oscillation Index), OLR (outgoing long-wave radiation) and MDR (main development region).

<i>Group</i>	<i>Predictors</i>	<i>Outputs</i>
CityU	<ol style="list-style-type: none"> 1. ENSO 2. Extent of the Pacific subtropical ridge 3. Intensity of India-Burma trough 	<ol style="list-style-type: none"> 1. Number of TCs 2. Number of named TCs 3. Number of typhoons
CSU	<ol style="list-style-type: none"> 1. SST North Atlantic 2. SST South Atlantic 3. SLP South Pacific 4. ENSO 5. Atlantic meridional Mode 	<ol style="list-style-type: none"> 1. Number of named TCs 2. Named of named TC days 3. Number of hurricanes 4. Number of hurricane days 5. Number of major hurricanes 6. Named of major hurricane days 7. Accumulated cyclone energy 8. Net tropical cyclone energy
INSMET	<ol style="list-style-type: none"> 1. North Atlantic winds 2. ENSO 3. Intensity of the Atlantic subtropical ridge 4. SST North Atlantic 5. Quasi Biennial Oscillation 	<ol style="list-style-type: none"> 1. Number of named TCs 2. Number of hurricanes 3. Number of named TCs in the Atlantic MDR, Caribbean and Gulf of Mexico (separately) 4. First day with TC genesis in the season 5. Last day with a TC active in the season 6. Number of named TCs that form in the Atlantic MDR and impact the Caribbean
ECMWF	<ol style="list-style-type: none"> 1. Coupled dynamical model 2. Model TCs identified and tracked 	<ol style="list-style-type: none"> 1. Number of named TCs 2. Mean location of TC genesis
IRI	<ol style="list-style-type: none"> 1. Various SST forecast scenarios. 2. Atmospheric models 3. Model TCs identified and tracked. 	<ol style="list-style-type: none"> 1. Number of named TCs 2. Accumulated cyclone energy (northern hemisphere only) 3. Mean location of TCs (western North Pacific only)
Macquarie U.	<ol style="list-style-type: none"> 1. SOI index 2. Equivalent potential temperature gradient 	<ol style="list-style-type: none"> 1. Number of TCs 2. Number of TCs in the Coral Sea
Met Office	<ol style="list-style-type: none"> 1. Coupled dynamical model 2. Model TCs identified and tracked 	<ol style="list-style-type: none"> 1. Number of named TCs
SMN	<ol style="list-style-type: none"> 1. SST anomalies 2. Equatorial wind anomalies 3. Equatorial Pacific OLR 	<ol style="list-style-type: none"> 1. Number of TCs 2. Number of tropical storms 3. Number of hurricanes 4. Number of major hurricanes
NOAA (Atlantic and Eastern Pacific)	<ol style="list-style-type: none"> 1. ENSO 2. Tropical multi-decadal mode 3. Atlantic SST 	<ol style="list-style-type: none"> 1. Number of named TCs 2. Number of hurricanes 3. Number of major hurricanes 4. Accumulated cyclone energy
NOAA (Central Pacific)	<ol style="list-style-type: none"> 1. ENSO 2. Pacific Decadal Oscillation 	<ol style="list-style-type: none"> 1. Number of TCs
Tropical Storm Risk (TSR)	<ol style="list-style-type: none"> 1. Trade winds 2. MDR SST 3. ENSO 4. Sea-level pressure central Northern Pacific 	<ol style="list-style-type: none"> 1. Number of named TCs 2. Number of hurricanes 3. Number of major hurricanes 4. Accumulated Cyclone Energy 5. ACE landfalling TCs 6. Number of landfalling named TCs 7. Number of landfalling hurricanes 8. Number of landfalling major hurricanes

the south-eastern USA (Lehmiller *et al.*, 1997). More recently, Elsner and Jagger (2006) built a Bayesian model for seasonal landfall over the USA, using as predictors May-June values of the North Atlantic Oscillation; the Southern Oscillation Index; and the Atlantic Multi-decadal Oscillation.

National Meteorological Service of Mexico

The National Meteorological Service of Mexico has produced a seasonal tropical cyclone activity forecast for the North-east Pacific basin since 2001. Their methodology uses analogue years and was originally developed by Arthur Douglas at Creighton University. The forecasts are first issued in January and updated in May, June and August. Various predictors are used, including SSTs and atmospheric circulation patterns over the North Pacific and outgoing long-wave radiation over the equatorial Pacific. A cluster analysis is then used to identify the most similar years in the historical record.

Australia/South-West Pacific

Forecasts for the Australian/South-West Pacific region are presented annually in the December issue of the Experimental Long-Lead Forecast Bulletin since the 2004–2005 season. These forecasts are based on a Poisson regression model and use as predictors the September saturated equivalent potential temperature gradient and the Southern Oscillation Index (McDonnell and Holbrook, 2004(a), (b)). They also developed forecasts for smaller subregions, among which the highest hindcast skill is in the Coral Sea, where ENSO has its strongest influence.

Other forecasts

The China Meteorological Administration has been issuing forecasts of typhoon activity for the

western North Pacific since the early 1980s. Since 1995, when the National Climate Centre was established, a nationwide workshop has been held in April. Forecasts for landfalling typhoons in the South China Sea and eastern China have also been developed. These seasonal forecasts are being continuously improved by the National Climate Centre and the Shanghai Typhoon Institute.

The North Carolina State University forecast group presented a new seasonal forecast methodology for Atlantic hurricanes at the 27th Conference on Hurricanes and Tropical Meteorology of the American Meteorological Society (T. Yan *et al.*, 2006) and gave their forecast for the 2006 season. These forecasts for number of hurricanes and number of landfalling hurricanes are based on ENSO, vertical wind shear, the Atlantic dipole mode and the North Atlantic Oscillation, as discussed in Xie *et al.* (2004, 2005).

It is likely that other statistical forecasts are being issued by various agencies around the world of which we are not aware.

Dynamical tropical cyclone seasonal forecasts

Many studies have shown that low-resolution climate models are able to simulate tropical cyclone-like disturbances (e.g. Manabe *et al.*, 1970; Bengtsson *et al.*, 1982). These disturbances have properties similar to those of observed tropical cyclones but are typically weaker and larger in scale. They are more realistic in higher-resolution simulations (e.g. Bengtsson *et al.*, 1995).

While low-resolution simulations are not adequate for forecasting individual cyclone tracks and intensities, some climate models have skill in forecasting levels of seasonal tropical cyclone activity. They are able to reproduce typical ENSO influences (e.g. Vitart *et al.*, 1997).

The International Research Institute (IRI) for Climate and Society, the European Centre for Medium-range Weather Forecasts (ECMWF) and more recently the UK Met Office issue experimental seasonal forecasts of tropical storm frequency based on dynamical models. The IRI and Met Office forecasts are freely available on the Web. The ECMWF forecasts are available online to collaborating agencies. The ECMWF and Met Office forecasts are based on coupled ocean-atmosphere models (Vitart and Stockdale, 2001). The experimental IRI forecasts are obtained using a two-tier procedure. First, various possible scenarios for SSTs are predicted, using statistical or dynamical models. Then, atmospheric models are forced with those predicted SSTs. In both cases, the tropical cyclone-like vortices are identified and tracked in the atmospheric model outputs (e.g. Camargo and Zebiak, 2002). The IRI also issues ACE forecasts based on dynamical models for several northern hemisphere regions. The IRI forecasts are probabilistic by tercile category (above normal, normal, below normal), as in the example for the Atlantic in 2006 (Figure 4). The rank probability skill score for the IRI July forecasts for the months of August to October in the Atlantic for the period 2003–2006 is positive with an approximate value of 0.12.

The skill of some of the best performing dynamical models in predicting the frequency of tropical storms is comparable to the skill of statistical models in some ocean basins. Over the North and South Indian Ocean, dynamical models usually perform poorly (Camargo *et al.*, 2005). It is not clear to what extent this is due to model errors or to a lack of predictability. Similarly to the seasonal climate forecasts, combining different model forecasts (multi-model ensemble forecasts) appears to produce overall better forecasts than individual model ensemble forecasts (Vitart, 2006). The hindcast skill of various dynamical climate models in predicting seasonal

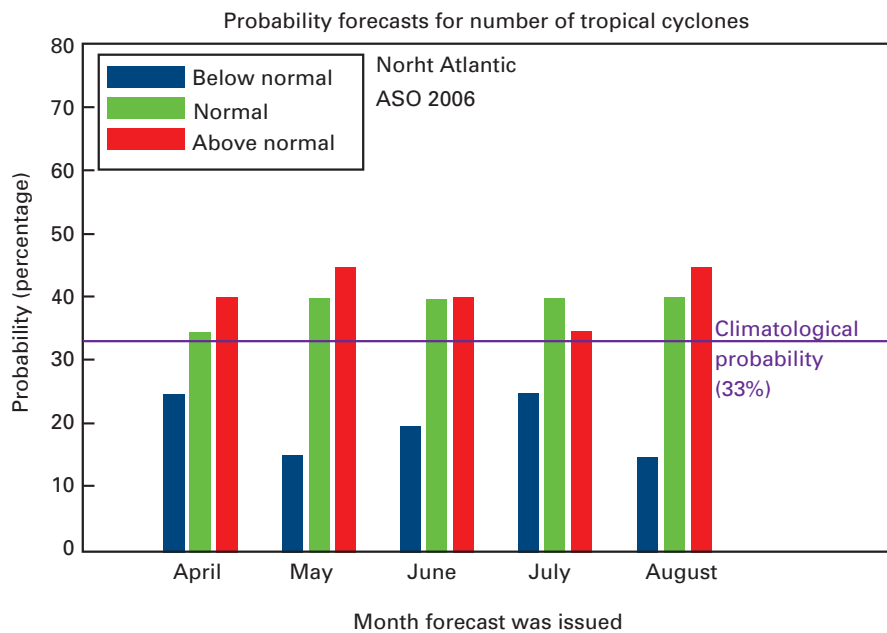


Figure 4 — IRI experimental dynamical forecast probabilities for the August-October (ASO) 2006 period in the Atlantic for different lead times. The normal category is defined as six to nine named tropical cyclones, the below-normal category as five or less named tropical cyclones and the above-normal category as 10 or more named tropical cyclones. In 2006 there were seven named tropical cyclones in the Atlantic during ASO, i.e. the season was in the normal category.

tropical cyclone activity is discussed in Camargo *et al.* (2005) and Vitart (2006). The European multi-model (EUROSIP) dynamical forecasts of tropical cyclone frequency skilfully distinguished the very active Atlantic hurricane season in 2005 from the below-average season in 2006 (Vitart *et al.*, 2007). The EUROSIP forecasts are not currently available to the public. The predicted number of tropical storms in the EUROSIP hindcasts (1993-2004) and real-time forecasts (2005-2006) is shown in Figure 5 (Vitart *et al.*, 2007, Figure 3).

Seasonal prediction of tropical cyclone landfall represents a major challenge for dynamical models. Tropical cyclones take an unrealistically poleward track in some of the models used in seasonal forecasting systems, due partly to the coarse horizontal model resolution, which leads to larger vortices than observed ones. These larger vortices would likely be more influenced by the beta effect. Finer-resolution climate models are able to reproduce landfall differences related to ENSO impacts, such as in

Mozambique (Vitart *et al.*, 2003). Another possible approach to predict the risk of tropical cyclone landfall using dynamical models would incorporate statistical techniques such as track clustering (Camargo *et al.*, 2007(a)).

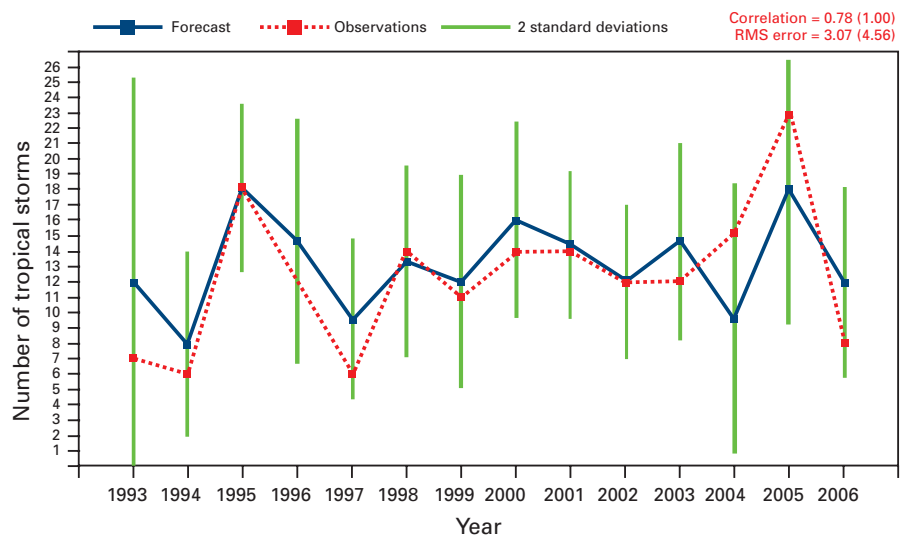


Figure 5 — Number of tropical storms from July to November predicted by the EUROSIP (median) starting on 1 June (blue solid line) for the period 1993-2006. Hindcasts were used for the period 1993-2004, and real-time forecasts in 2005-2006. The observations are given in the dotted red line and the green vertical lines represent two standard deviations within the multi-model ensemble distribution. (Figure originally from Vitart *et al.*, 2007)

An alternate approach for forecasting tropical cyclones using climate models involves simulating the interannual variability of environmental variables that affect tropical cyclone activity (e.g. Ryan *et al.*, 1992). A drawback of this approach is that it requires a choice of which variables or combinations of variables should be analysed. Recently, a few studies compared both approaches using the same climate models (e.g. McDonald *et al.*, 2005; Camargo *et al.*, 2007(b)). Both approaches may be used in the future, since they are complementary.

The importance of ENSO prediction

ENSO events shift the seasonal temperature and precipitation patterns in a consistent manner in many parts of the world (Bradley *et al.*, 1987; Ropelewski and Halpert, 1987). Depending on the time of the year, ENSO phenomena can be predicted with modest-to-moderate skill months in advance (Cane and Zebiak, 1985). ENSO forecasts are routinely used as a major component in probabilistic seasonal climate forecasts at various centres (Goddard *et al.*, 2001).

Tropical cyclones are also affected by ENSO in various parts of the world. The relationship between them was first documented in a series of papers by Neville Nicholls for the Australian region (Nicholls, 1979). During warm ENSO events, fewer cyclones occur near Australia, while in cold events, an enhanced risk of landfall in Australia exists with more cyclones affecting Queensland. The impact of ENSO on North Atlantic cyclones was first discussed by William Gray (Gray, 1984(a)). The influence of ENSO on western North Pacific typhoon activity was first explored in Chan (1985). In all cases, the relationship of ENSO and tropical cyclones was subsequently developed into statistical forecasts predicting seasonal activity.

The state of ENSO is of fundamental importance in the seasonal activity level and character of tropical cyclones in all ocean basins. This is the case not only because of the obvious relevance of the ENSO state to the SST anomaly pattern in the tropical ocean basin but also because of the influence of ENSO on fields of local atmospheric variables, such as the large-scale horizontal pattern of anomalous circulation and geopotential height, upper-level divergence and vertical wind shear. Thus, our ability to predict ENSO state several months in advance is critical to being able to predict tropical cyclone activity in the same timeframe, using either statistical or dynamical methodologies.

ENSO predictability follows a well-known seasonal cycle, in which the ENSO state for 4-6 months into the future is more accurately predicted from a starting time between July and November than between January and March. This is due to a "predictability barrier" that exists between April and June, such that forecasts made just before this period are hindered by the barrier. The seasonal timing of the predictability barrier is related to the life cycle of ENSO episodes, which often emerge between April and June and endure until the following March to May. Once an episode has begun,

predicting its continuation for the next 9 to 12 months is a much easier task than predicting its initial appearance. Even a strong El Niño, such as that of 1997/1998, was not well anticipated before signs of the initial onset were observed in the northern hemisphere spring of 1997 (Barnston *et al.*, 1999). Even after becoming apparent in the observations in late April and May 1997, the strength of this extreme El Niño event was underpredicted by most models, although a few models did correctly anticipate the rapid weakening in the spring of 1998 (Landsea and Knaff, 2000).

There is varying skill in ENSO forecasts as evidenced by the Nino3

forecasts obtained with the Zebiak and Cane (1987) simple coupled model (Figure 6). While these skills are for a particular model, they roughly approximate the skills for predictions of other dynamical as well as statistical models, because they represent basic predictability that is reflected similarly across most of the present models. It is clear that predictive skill for forecasts made in March is high for only 2-3 months, while, for forecasts made in August, the skill extends to longer lead times. Improvements in predictive skill using today's more advanced dynamical models have been small and it remains to be seen whether or not substantial improvements

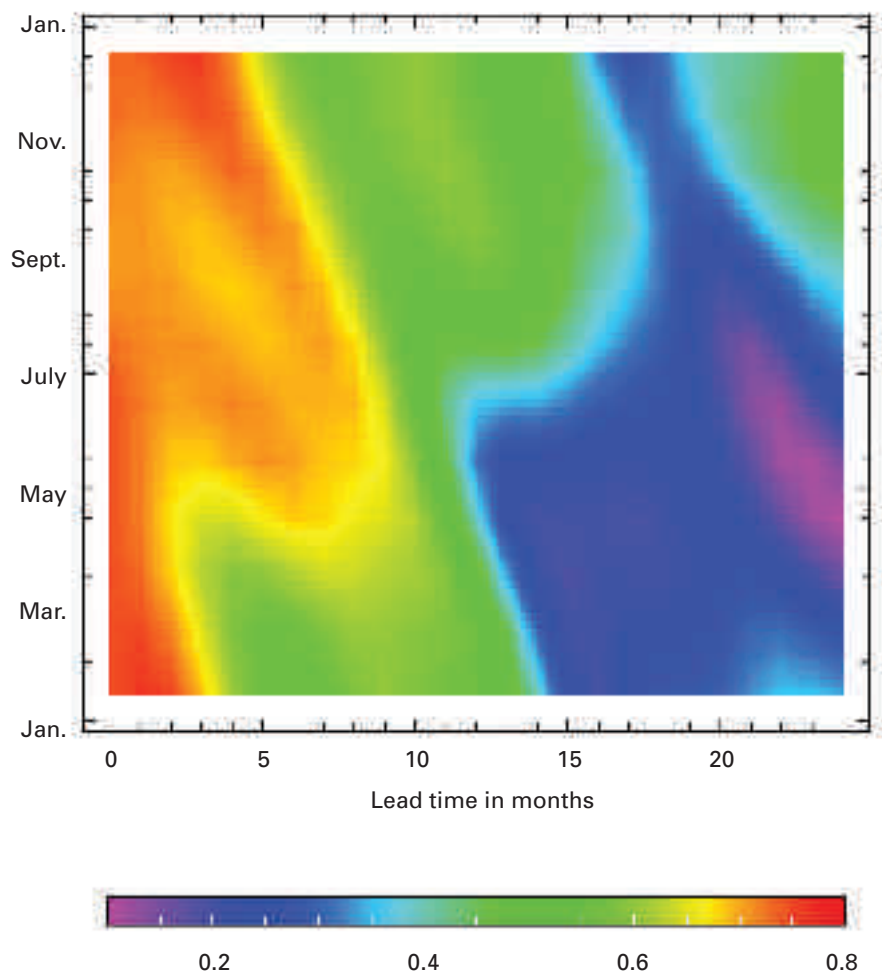


Figure 6 — Skill of the Zebiak and Cane ENSO forecast model for prediction of Nino3 sea-surface temperature anomalies for varying hindcast start months and hindcast lead time. The colours indicate skill as a correlation between the hindcasts and the corresponding observations. The vertical axis indicates the month from which the hindcast is made and the horizontal axis is the lead time. For example, a hindcast made from July with a lead time of two months would be a hindcast for September and with a lead time of 24 months (right side of figure) would be a hindcast for the July two years after the hindcast was made.

are possible, given the inherent signal-to-noise characteristics of the ocean-atmosphere system. The “slow physics” relevant to ENSO dynamics may become better predicted by both statistical and dynamical models of the future. However, better prediction of the shorter time-scale events that can also be important in triggering El Niño onset, such as the Madden-Julian Oscillation, may prove to be nearly impossible at multi-month lead times. The May forecasts by many statistical and dynamical models for the El Niño event of 2006/2007 are shown in Figure 7. Very few models were able to forecast this event, which had a late onset and was not very strong.

The ENSO predictability barrier has clear-cut implications for predictions of tropical cyclone activity in the northern hemisphere when compared to predictions of activity in the southern hemisphere. Tropical cyclone activity in the northern hemisphere is considerably more challenging to predict because its peak seasons occur shortly after the ENSO predictability barrier. When an ENSO event appears somewhat later than usual (as was the case in the late northern hemisphere summers of 1986 and 2006), the inhibiting effect on North Atlantic tropical cyclones is unanticipated until the peak season of August to October is already beginning. This can necessitate a sudden change as a final update to the seasonal prediction and can potentially disrupt plans already being followed in accordance with an earlier seasonal prediction.

The peak season for southern hemisphere activity occurs at least 6 months after the northern hemisphere spring ENSO predictability barrier, which provides a safer cushion of lead time in which to become fairly certain about the ENSO state to be expected during the peak season. Thus, last-minute surprises in seasonal outlooks for basins south of the Equator are less likely to be impacted by inaccurate ENSO outlooks. Nonetheless, it is clear that a major hurdle in improving

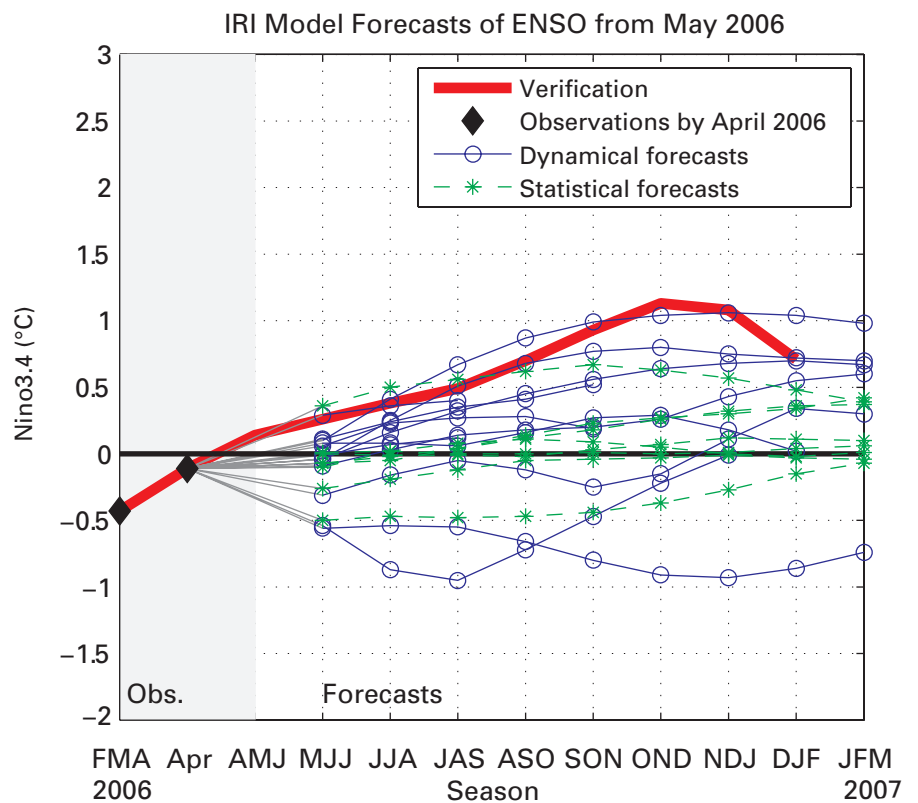


Figure 7 — May 2006 statistical and dynamical forecasts for the Nino 3.4 index (anomalies) using April observations. Observations for the Nino 3.4 region are also shown.

predictions for any ocean basin is the far-from-perfect quality of today’s state-of-the-art ENSO forecasts. Indeed, Landsea and Knaff (2000) showed that it is still very difficult to outperform a simple statistical model that uses as predictors only the recent evolution of SST anomalies in a few tropical Pacific regions. This modest skill level for detecting El Niño onset still exists in 2007, as demonstrated by the poor predictions of the late-starting 2006/2007 El Niño (Figure 7). If the ENSO forecast challenge could be overcome, the skill of predictions could improve significantly—most notably in the northern hemisphere.

Verification and evaluation of seasonal tropical cyclone forecasts

As for predictions of any aspect of seasonal climate, predictions of tropical cyclone activity are

subject to legitimate verification and evaluation (Hastenrath, 1990; Owens and Landsea, 2003). Verification measures help communicate the quality of future predictions to users who need to know how to reasonably apply them in their decision-making processes. Predictions of tropical cyclone activity are expressed deterministically (e.g. a forecast of either the exact number of tropical cyclones or a specific range of their numbers in a given ocean basin during the peak season) or probabilistically (e.g. forecast probabilities for an underactive, a near-normal or an over-active season). Suitable verification measures for past predictions of the same kind given in real-time and/or properly cross-validated hindcasts over an extended past period during which real-time forecasts were not issued, are an absolute necessity. Even the best attempts at cross-validation may produce a somewhat too optimistic skill estimate relative to the skill expected for real-time forecasts (Barnston *et al.* 1994).

Given the widespread dissemination of new seasonal tropical cyclone forecasts, it is fundamental that all forecast agencies should follow standard guidelines for producing and verifying these forecasts. A Website is currently being developed that will include seasonal climate forecasts issued by various agencies. To participate, the agencies must follow the WMO guidelines for seasonal forecasts. At the IWTC-VI meeting in Costa Rica, it was suggested that a similar Website could be developed for seasonal tropical cyclone forecasts. Guidelines and standards must first be developed such as for other seasonal climate forecasts.

One necessary step is to define common metrics for the seasonal tropical cyclone forecast outputs, such as number of named storms, number of hurricanes, number of major hurricanes, and accumulated cyclone energy). Dynamical forecasts currently do not issue forecast number of hurricanes and major hurricanes, mainly because of the low resolution of the models, but that could be achieved in the future with higher resolution models. Some forecast variables produced by individual groups, such as number of hurricane days, would not be required for all agencies.

Another important consideration for setting up guidelines for tropical cyclone seasonal forecasts is the verification measures. Table III has a list of skill measures that could be used. It is emphasized that a combination of various skill measures gives a more complete evaluation of the skill of the forecasts.

Verification measures are often formulated as a comparison with a set of reference forecasts made using a much simpler and uninformed method, such as perpetual climatology forecasts or perpetual persistence of observations from the previous year or averaged over the previous n years. Such so-called “skill scores” are often scaled to be zero when the

actual forecasts attain skill equal to that of the reference forecasts and one (or 100 per cent) when they are perfectly accurate. The choice of a reference forecast is vital to an understanding of the meaning of the skill score. Climatology is often used as the reference forecast—a forecast for the long-term mean number of tropical cyclones as a deterministic forecast or a forecast for climatological probabilities (e.g. 33.3 per cent for each of the tercile-based categories) as a probabilistic forecast.

Outperforming a climatology reference forecast is not usually considered difficult when some predictive skill is assumed to exist. On the other hand, setting the reference forecast to be the skill of a statistical model in verifying a dynamical model could be setting the reference forecast standard too high. Statistical models may be able to capture much of the available predictability inherent in the climate system through the observed historical data. Table III has a suggested list of verification measures for deterministic and probabilistic forecasts.

Examples of verification measures that have commonly been used with climatology forecasts as the reference are the mean square error skill score (MSESS; WMO, 2002) and the ranked probability skill score (RPSS;

Epstein, 1969) for deterministic and probabilistic forecasts, respectively. The conventional (i.e. Pearson) correlation coefficient or the Spearman rank correlation coefficient are also informative when applied to deterministic forecasts. When the correlation is applied to a small subset of a much longer climatological base period, the uncentred correlation coefficient, where the climatological mean is not removed in computing the standard deviations and subsequently for the deviations of the cross-products, may be a more suitable verification measure than the standard correlation. This is particularly true when the mean values for the sub-period differ noticeably from the overall climatological means.

In the case of dynamical forecasts, the skill of hindcasts should be provided (e.g. Camargo *et al.*, 2005). For statistical prediction methods, cross-validation (Michaelsen, 1987) is needed to help reduce artificial skill that can exist in the training data sample but vanishes when the method is applied to a real-time forecast for the future. Statistical methods optimize results within the training sample and cannot filter out the component of skill related to fitting the adjustable parameters (such as the weighting of each of the predictors in a multiple linear regression technique) to the random variations in the sample being

Table III — Verification skill scores suggested for deterministic and probabilistic TC activity seasonal forecasts. Most of these scores are described in standard statistical books, such as Wilkes (1995). The natural categories skill score is in Owens and Landsea (2003), while the likelihood score is described in Harte and Vere-Jones (2005).

Type of Forecast	Verifications : skill scores
Deterministic	<ol style="list-style-type: none"> 1. Root mean square error skill score 2. Pearson correlation coefficient 3. Spearman rank correlation coefficient 4. Uncentred correlation coefficient (short periods) 5. Bias compared to climatology 6. Percentage improvement over trend 7. Normalized natural categories skill score
Probabilistic	<ol style="list-style-type: none"> 1. Ranked probability skill score 2. Relative operating characteristic (ROC) skill score 3. Likelihood skill score

used. In cross-validation, forecast models are derived from all cases except for one (or more) that are withheld, and these cases are then used as the target(s) of the prediction. This is repeated with all possible cases, or sets of cases, withheld and used as the target(s). The anomaly values of the cases withheld must be expressed in terms of the climatology formed from the remaining years, which changes slightly each time a new case(s) is withheld.

Skill estimates resulting from cross-validated forecasts are nearly always somewhat lower and more indicative of skills to be expected in future cases. When true skill is very high (e.g. the correlation between forecasts and corresponding observations > 0.6), cross-validation results in only slightly lower skill than those in the training sample. When true skills are low (e.g. 0.2 to 0.4), cross-validation results are markedly lower and occasionally negative.

Skill estimates produced using cross-validation may be used to dampen the amplitude of real-time statistical forecasts that use an entire training sample for predicting a future case in real-time. Such damping helps hedge against some artificial skill that may be present in the real-time forecast. For example, if a real-time regression forecast has an expected skill of 0.5 (as indicated by the variance explained by the model using all available past years for training) but the cross-validated correlation skill score for the same model is 0.4, then the amplitude of the anomaly of the real-time forecast for a future month would be decreased by the factor of 0.4/0.5 or 0.8 to account for the over-confidence associated with over-fitting to the finite data sample.

One important aspect to keep in mind is that different tropical cyclone regions have very different potential predictabilities. These differences are due to various factors, such as the basin climatological characteristics, the strength of the basin relationship

with ENSO and the timing of the basin tropical cyclone season relative to the ENSO cycle. Further research is necessary to gain a clear picture of this potential predictability. Unfortunately, the inhomogeneity of best-track datasets and possible biases in dynamical models prevent an accurate estimate of the potential predictability.

Summary

Statistical seasonal tropical cyclone forecasting has come a long way since it began in the early 1980s. Along with predictions of total seasonal activity, several forecasts now include individual monthly forecasts and predictions of probability of landfall. As the availability of global datasets such as the various re-analysis products continues to be improved, so will statistical forecasts of tropical cyclones. An updated and homogenous quality global best-track dataset would also contribute to more skilful forecasts (Landsea *et al.*, 2004; Kossin *et al.*, 2007).

Dynamical seasonal tropical cyclone forecasts are now currently issued for various regions. Increasing model resolution should help improve the skill of these forecasts. To be able to forecast landfall probabilities using dynamical models where possible, systematic biases in the tracks of model tropical cyclones need to be examined, explained and corrected. Some of the biases are probably due to factors other than low resolution and more research is needed in understanding the atmospheric model ability to forecast tropical cyclones.

Future improvement of seasonal forecasts is strongly dependent on improving ENSO forecasts, including greater detail about the characteristics of the ENSO event such as its magnitude, location and spatial pattern of SST anomalies. Both statistical and dynamical forecasts are dependent on the quality of ENSO forecasts for some of their skill.

Currently, various agencies are issuing tropical cyclone forecasts. It is of fundamental importance to establish standards for the development and verification of these forecasts, so that users are able to apply them appropriately. A single Website could be developed by WMO to give easy access to all forecasts that follow the WMO guidelines.

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