Technical newsletter June 2014

Seasonal hurricane forecast skill and relevance to the (re)insurance industry

Seasonal hurricane forecasts are eagerly anticipated each year by coastal residents and businesses, emergency management agencies, and of course insurers, reinsurers and holders of US wind exposed Cat Bonds. In view of the potential societal impact of hurricanes, forecasting techniques are discussed widely in the scientific literature, where several different forecasting approaches have been put forward (Gray 1984; Elsner and Jagger 2006; Vitart 2006; Wang et al. 2009; Saunders and Lea 2005; LaRow et al. 2010; Vecchi et al. 2011). Many of these approaches are implemented by forecasting groups that provide regular and publicly available seasonal forecasts. The performance of forecasts in the 2013 season was unsatisfactory where hurricane activity was significantly overestimated by all. This raises the central question: "How skillful are seasonal forecasts?" that this paper addresses by comparing past forecasts with observed hurricane activity and introducing the reader to statistical measures of "skill". We also consider the application of these forecasts to the (re)insurance industry.

Introduction

This paper evaluates the forecasts of the Colorado State University (CSU), the Climate Prediction Center (CPC) and the Tropical Storm Risk (TSR), who have been issuing real-time forecasts for more than a decade. These groups forecast a number of different quantities. CSU forecasts, among other metrics, the number of hurricanes expected in the upcoming season, officially defined for the Atlantic as the period starting on June 1st and ending on November 30th. Further useful forecast quantities are the Accumulated Cyclone Energy (ACE) (CPC 2001) assessed by CPC and TSR and the Net Tropical Cyclone Activity (NTC) (Gray et al. 1994) provided by CSU. Both ACE and NTC aim at capturing seasonal tropical storm activity in a metric that contains information on both the intensity and the duration of all basin tropical storms (see *Info Box 1* for definitions). The observed ACE and NTC values between 2001 and 2013 exhibit a correlation of 0.96, implying that although the two metrics are not identical, they capture fundamentally the same information. All forecast data presented here are publicly available and have been downloaded from the respective websites of CPC, TSR and CSU.

The three forecasts examined here are based on different methodologies. The TSR forecast is based on a statistical model where the predictor variables are forecasts of trade winds and sea surface temperature in certain parts of the Atlantic. The forecasts of the predictor variables in turn are obtained from other dynamical and statistical models. The CSU forecast also uses a statistical model with a limited set of predictor variables that include observed and forecast quantities. The statistical model output is subsequently adjusted using an analog scheme and further qualitative methods. The CPC forecast is based on a hybrid method of a statistical model and dynamic models that directly predict seasonal hurricane activity.

Info Box 1

Measures of tropical storm activity

Hurricane Day (HD): this quantity is defined by the CSU group as "a measure of hurricane activity, one unit of which occurs as four 6-hour periods during which a tropical cyclone is observed or is estimated to have hurricane-force winds". Named Storm Day (NSD) and Major Hurricane Day (MHD) are defined similarly.

Net Tropical Cyclone (NTC) activity: average seasonal percentage mean of the number of tropical storms, the number of hurricanes, the number of major hurricanes, NSD, HD and MHD. NTC gives an overall indication of Atlantic basin seasonal hurricane activity. The 1950-2000 average value of this parameter is 100.

Accumulated Cyclone Energy (ACE): The ACE of a season is calculated by summing the squares of the estimated maximum sustained velocity of every active tropical storm (wind speed 35 knots (65 km/h) or higher), at six-hour intervals. The result is then multiplied by 10^{-4} to make the numbers more manageable. The unit of ACE is $10^4 kn^2$.

Info Box 2

Some commonly used methods in seasonal hurricane forecasting

Statistical forecasting: A relationship between a metric of hurricane activity and a selected set of predictors is established using past observations. The values of the predictors in the year in question are then plugged into the relationship to get an estimate of the hurricane activity in the upcoming season. See *Info Box 3* for some important predictors of hurricane activity.

Analog forecasts: These are based on identifying one or more previous seasons with atmospheric conditions similar to the season in question. The hurricane activity eventually observed in the previous selected season(s) can either be used as a forecast for the season in question or it can influence the result in a forecast method that takes into account further considerations.

Dynamic forecasts: These are based on models that use (simplified) sets of time-dependent equations describing the physical behavior of the atmosphere-ocean system. An estimate of the future state of the system (including hurricane activity) is obtained by solving these equations.

Info Box 3

Some important predictors of hurricane activity in statistical forecasts

Forecast of the sea surface temperature in parts of the Tropical and Subtropical North Atlantic during the hurricane season: High sea surface temperature enhances hurricanes by increasing the energy that is available for their development.

Sea level pressure in Central/Eastern Subtropical North Atlantic in the months before the hurricane season: Increased sea level pressure leads to stronger trade winds, which in turn result in lower sea surface temperature. Lower sea surface temperature creates a positive feedback by increasing sea level pressure. This mechanism eventually contributes to lower sea surface temperature during the hurricane season and therefore reduced hurricane activity.

Forecast trade wind or wind shear over the Tropical and Subtropical North Atlantic region during the hurricane season: Increased vertical wind shear inhibits hurricanes by distorting their vertical structure. Various theories have been put forward to explain this phenomenon from a physical point of view (Tang and Emanuel 2010).

Forecast sea surface temperature in parts of the Pacific Ocean or forecast of the El Niño during the hurricane season: Increased sea surface temperature in certain areas of the Pacific or El Niño conditions lead to enhanced wind shear in parts of the Atlantic. As described above, wind shear inhibits hurricane activity.

See *Info Box 2* for a brief description of forecast methods and *Info Box 3* for some important predictors of hurricane activity.

Seasonal forecasts are released at various dates ranging from December until August. The December forecasts are particularly challenging since it is very difficult to predict crucial parameters that affect hurricane activity, such as El Niño, a long time in advance. In this paper, forecasts issued around the beginning of the hurricane season (late May for CPC and CSU and early June for TSR, hereafter referred to as the May-June forecasts) are compared to observations. The same is also undertaken for forecasts issued beginning of August by all three groups. In addition, the April and July forecasts of TSR are briefly discussed.

A further objective of this study is to link seasonal forecasts with insurance losses. Pielke and Landsea (1999) have shown a relationship between El Niño as a predictor of hurricane activity and economic losses. Simmons and Saunders (2005) implemented a method to adjust insurance loss probabilities based on August hurricane forecasts. An attempt will be made to assess the ability of the August forecasts to estimate insurance losses using the real-time forecasts up to 2013. U.S. industry loss data have been obtained from Property Claim Services (PCS) and they have been indexed to account for changes in housing/population, consumer price index and insurance penetration. Given that insurance losses are more strongly related to hurricane landfalls than basinwide activity, forecast landfall probabilities [1] and number of landfalls issued by CSU and TSR will be evaluated.

Method

Seasonal forecasts are evaluated using a number of simple performance measures. Systematic error is estimated using the bias statistic defined as: $B = \bar{y} - \bar{o}$, where $\bar{y}$ is the average of forecast values over the evaluation period and $\bar{o}$ is the average of the observations. The deviation of forecasts from individual observations is quantified using the Mean Absolute Error (MAE) defined as: $MAE = \frac{1}{N}\sum_i |y_i - o_i|$ where y_i is the forecast for the *i-th* season, o_i is the observation for the same season and N is the total number of seasons being evaluated. For example, a seasonal hurricane forecast with MAE=1.0 over- or under-predicts the number of hurricanes in a season by 1 hurricane on average. The correlation between forecasts and observations (as well as hurricane activity and insurance losses) is evaluated using Kendall correlation coefficient. Its calculation is based on the order of each datum in the two datasets that are compared and it is defined as: $\tau = \frac{C-D}{C+D}$, where C is the number of concordant pairs and D is the number of discordant pairs [2]. Kendall's τ was selected as a measure of association because of its ability to handle non-linear monotonic relationships and because it is particularly easy to interpret as the percentage of concordant pairs minus the percentage of discordant pairs.

Seasonal forecasting approaches are updated regularly to account for the latest scientific developments and for changes in the environmental factors that affect hurricane activity. This implies that the skill of

1 Landfall probabilities by CSU are directly related to the forecast values of NTC.

2 A concordant pair is a pair of a two-variable data set $\{X_1, Y_1\}$ and $\{X_2, Y_2\}$, where: $sign(X_2-X_1) = sign(Y_2-Y_1)$. Correspondingly, a discordant pair is a pair, as defined above, where $sign(X_2-X_1) = -sign(Y_2-Y_1)$.

past forecasts is not an accurate measure of the skill of a new, updated forecasting scheme. Forecasting methods are often assessed by hindcasting, i.e. by running a forecast for past seasons and assessing its performance comparing to the known hurricane activity. However, a forecasting scheme with good hindcast results can fail when the actual outcome is influenced by changing or previously unknown predictors and when the past data used to calibrate the forecast are incomplete or inaccurate. Therefore, a more complete picture regarding forecast performance can be obtained if both hindcasts and real-time forecasts are evaluated. CSU provide the longest running forecast, issued since 1984. Klotzbach and Gray (2009) investigated its real-time performance using 25 years of data. All three forecasting groups discussed in the present study have been consistently issuing quantitative real-time forecasts in May-June and in August each year since 2001. Here we take advantage of the opportunity that is offered by more than a decade of seasonal hurricane forecasting to assess and intercompare real-time forecast performance. Although 13 years of data are not enough to reach any definitive conclusions, they are deemed sufficient to get a first impression of seasonal forecast accuracy.

Each of the examined forecasting groups has a different approach to communicating forecast uncertainty. CSU provides a single "best" estimate of basin activity[3]. TSR provides a best estimate together with an uncertainty range whereas CPC provides only a likely range of activity. In order to facilitate comparison with the other forecasts, the mean of the range provided by CPC is used for the evaluation of the "best" deterministic estimates.

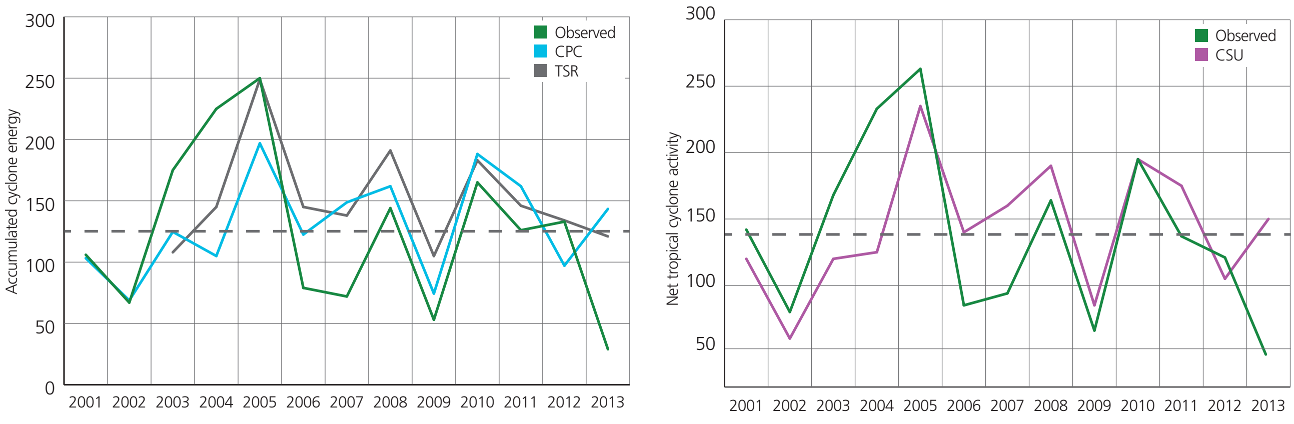
Results

Figure 1 provides an overview of seasonal ACE/NTC August forecasts and observations. The evaluation period is 2001-2013 except for the TSR ACE values that are only available since 2003. The skill of individual forecasts varies considerably depending on the year. The 2005 forecast was a notable success for the TSR group that predicted an extremely active season accurately. In general, both successful seasons (e.g. 2010) and less successful seasons (e.g. 2004) have been observed. The performance of all forecasts in terms of bias is summarized in *Table 1.* Forecast bias is in general small with the exception of the TSR August forecast that tends to over-predict hurricane activity. As shown in *Figure 2,* the August forecasts usually have smaller error than the May-June forecasts, although there are a couple of instances for each group where the opposite was true. The difference between the August and May-June forecast tends to be smaller for the CPC and CSU forecasts compared to TSR. The Mean Absolute Error statistics are summarized in *Table 2.* The August forecast represents an improvement over the May-June forecast for all groups investigated. The MAE value of the May-June TSR ACE forecast is 51, which is slightly better than the CPC MAE value of 54 (for comparison, the 2001-2013 ACE mean value is 125). However, the CPC May-June forecast has the disadvantage of being issued about 2 weeks before the corresponding TSR forecast. The three examined forecasts are strongly associated to each other. This is particularly true for the CSU and CPC August forecasts of the number of hurricanes, which exhibit a Kendall's correlation coefficient of 0.92. The CSU and CPC forecasts have a somewhat lower correlation with the TSR forecast (0.73 and

Table 1. Bias of seasonal forecasts compared to the observed averages. The averaging period is 2001-2013 except for the TSR ACE where the 2003-2013 period has been used.

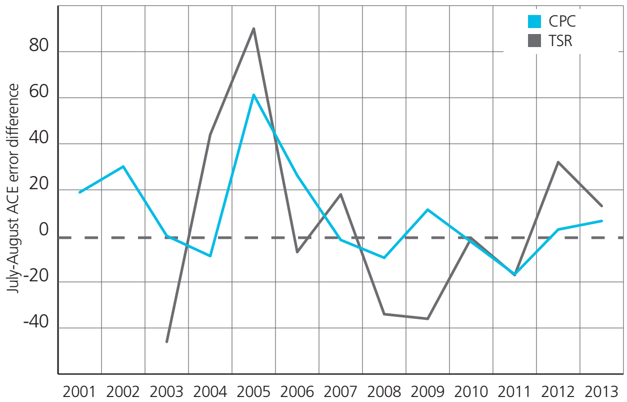
	ACE	NTC	n.o. hurricanes
CSU May-June	-	12	0.3
CPC May-June	1	-	0.2
TSR May-June	-1	-	-0.4
CSU August	-	5	0
NOAA August	3	-	0.1
TSR August	26	-	0.2

Figure 1. Time series of August forecasts and observations of ACE (left) and NTC (right). The solid horizontal lines represent the mean of the 2001-2013 observations (125 for ACE and 138 for NTC).



3 CSU do provide an uncertainty range in the statistical forecasting stage of their forecast scheme. This could be used as an approximate uncertainty range for the final forecast too.

Figure 2. Difference (May-June minus August) of the absolute forecast error of the TSR and CPC ACE forecasts (left) and the CSU NTC forecasts (right). Positive values indicate that the August forecast has a smaller absolute error than the May-June forecast.



0.78 respectively). In *Table 2* the skill of using the average activity as a forecast can be evaluated as well. The performance of the recent (2001-2013) average is comparable to that of the May-June forecasts while the August forecasts represent an improvement over climatology.

Another view on the forecasting horizon has been taken by adding the April and July TSR forecasts in the investigation. *Figure 3* shows MAE values for each forecast month calculated from the TSR ACE forecasts. If forecasts are compared to recent climatology, forecasts from June on represent an improvement whereas the April forecasts do not.

Given that forecast methods are frequently updated, it is interesting to look at how forecast error evolves with time. *Figure 4* shows the MAE of the three assessed forecasts for each year. A decreasing trend is evident for the period after 2005/2006, however this trend stops with the large error of the 2013 forecasts. This finding is compared with the evaluation of the CSU forecast for the period between 1984 and 2008 by Klotzbach and Gray (2009). Based on the hurricane day statistic *(Info Box 1)* examined in that study, no improvement with time can be seen in the June and August forecast skill *(Figure 5)*. Here one should note that hurricane activity in years after 1994 has increased considerably compared to the period between 1971 and 1994 (Goldenberg et al. 2001). A forecast improvement may still be present but difficult to detect because there is much larger variation in ACE values during the active era since 1995 than in the inactive era before.

Table 2. Mean Absolute Error of various metrics of hurricane activity. Climatological/recent averages and forecast values are presented. As a reference, the mean value of ACE, NTC and number of hurricanes over the 1950-2013 period is 102, 107 and 6.2 respectively.

	ACE	**NTC**	**n.o. hurricanes**
1950-2013 average	55	56	2.9
1980-2013 average	55	55	2.9
2001-2013 average	53	52	2.8
CSU May-June	-	52	2.9
CPC May-June	54	-	2.9
TSR May-June	51	-	2.6
CSU August	-	42	2.3
CPC August	45	-	2.3
TSR August	46	-	2.3

Figure 3. Evolution of the MAE of TSR ACE forecast per forecast issue month for the period from 2003 until 2013. Horizontal dash line indicates the MAE of the 2001-2013 average. The solid line represents a least squares fit. May forecasts have been left out because of missing data.

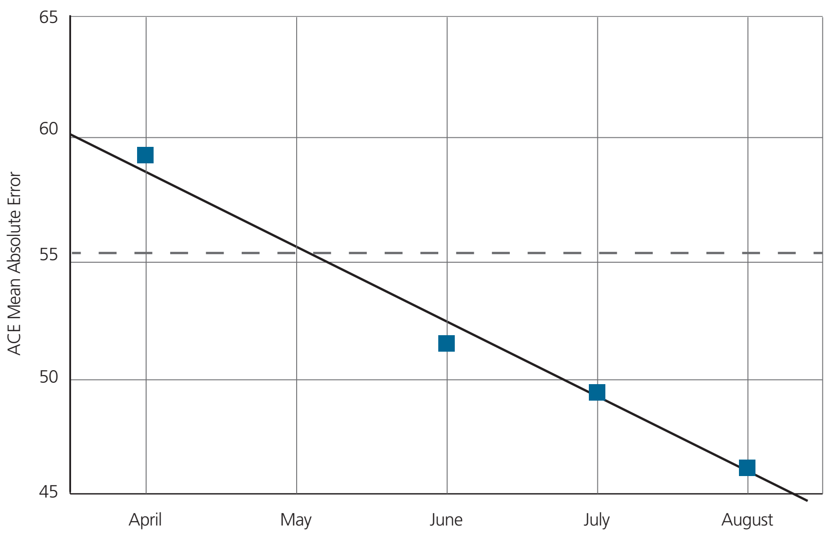


Figure 4. Absolute error of the CPC and TSR August forecasts (left) and the CSU forecast (right).

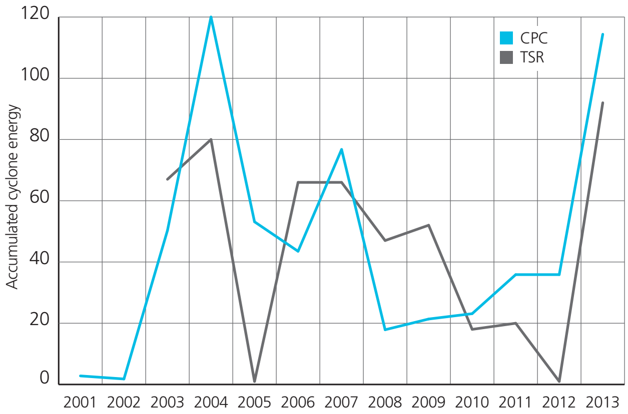
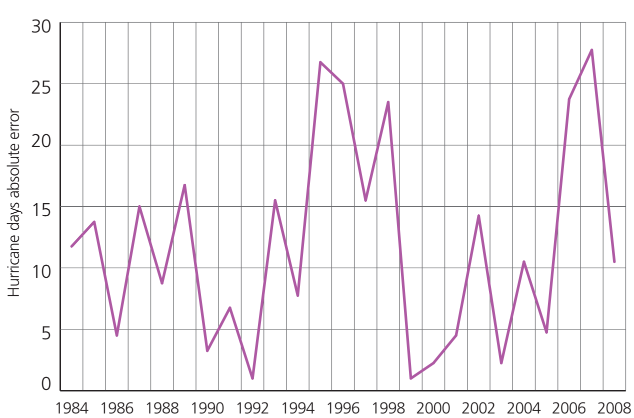


Figure 5. Absolute error of the CSU June (left) and August (right) forecast of hurricane days. Data extracted from Klotzbach and Gray (2009).



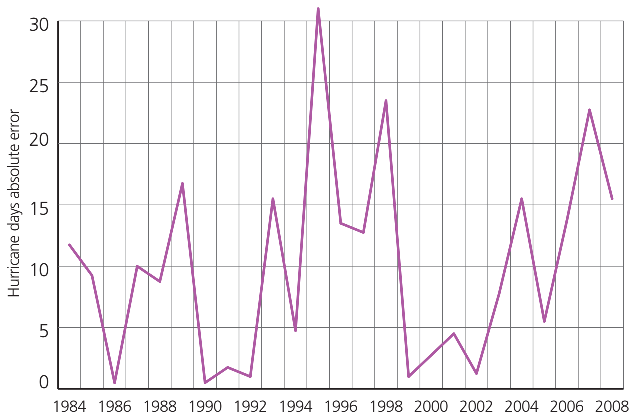


Table 3. Kendall's tau correlation coefficient between observed and forecast hurricane activity. Bold numbers in green color indicate significant correlation at the 95% level of confidence.

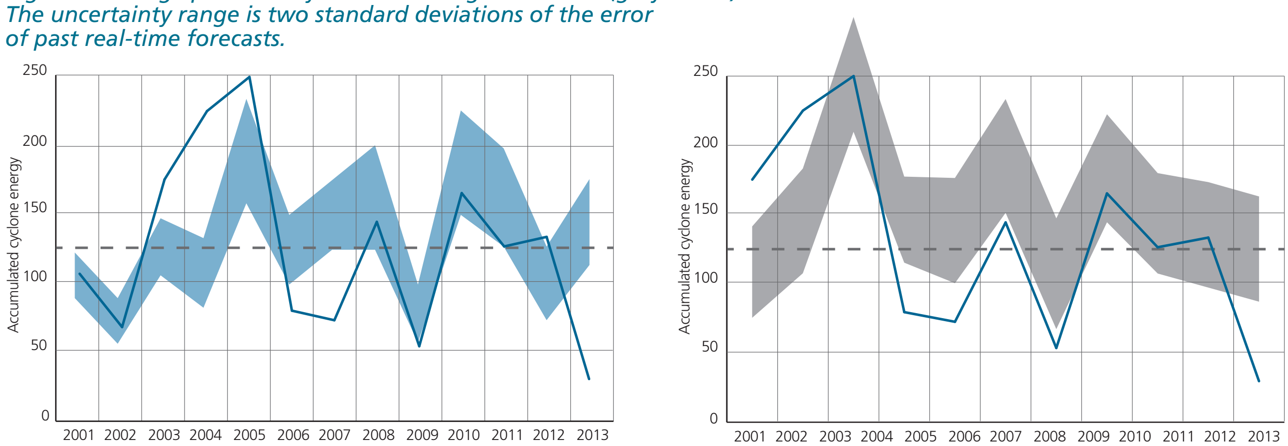
	ACE	NTC	n.o. hurricanes
CSU May-June	-	0.11	-0.04
CPC May-June	-0.01	-	-0.09
TSR May-June	0.20	-	0.13
CSU August	-	**0.43**	0.36
CPC August	0.35	-	0.36
TSR August	0.44	-	0.32

The correlation between observed and forecast hurricane activity is summarized in *Table 3.* The May-June forecasts have a negligible correlation with observed activity with the exception of the TSR ACE estimates that exhibit a correlation of 0.20. The August forecasts have higher correlations that exceed 0.30 and are deemed to be informative to some extent. The CSU NTC August forecast is the only forecast with a statistically significant correlation to the observations. In general it is difficult to obtain statistically significant correlations with the relatively small sample size available for this study. This is even more the case for the TSR ACE forecasts that are only available since 2003.

It is instructive to validate the uncertainty ranges provided by different forecasting groups in addition to the best estimates. CPC provides likely activity ranges indicating that actual hurricane activity is expected to fall within the provided ranges in 70% of the seasons. TSR provides the standard deviation of the errors in replicated past real time forecasts. If an uncertainty range of two standard deviations is constructed around the best estimate, it is expected that actual forecasts fall within the range 67% of the time. *Figure 6* shows the uncertainty ranges provided by the two groups along with the actual outcome. Observations fall outside the forecast activity range most of the time for both groups. This could indicate that past observations used to calculate forecast error no longer correspond to recent hurricane activity.

In addition to forecasts of basin activity, CSU and TSR issue forecasts of hurricane landfalls. Forecasting hurricane landfalls presents forecasters with additional challenges since further aspects of hurricane activity (such as regionalized activity and steering currents) need to be estimated too. CSU forecasts the annual probability of one or more continental US major hurricane landfall during the season. The August forecasts range between 46% and 77% in the 2001-2013 period. Nevertheless, there

Figure 6. Left: ACE range predicted by CPC in the August forecast (blue shade) and observed values. For each forecast, actual activity is expected to fall within the provided range 70% of the seasons. Right: ACE range provided by TSR in the August forecast (grey shade) and observed values. The uncertainty range is two standard deviations of the error of past real-time forecasts.



have been only two years with one or more major landfalls in the same period. *Figure 7* shows the error range of TSR landfalls along with the corresponding observations. The observations fall within the error range in 5 out of 11 seasons. The observed mean is 1.5 US landfalls per year whereas the forecast mean is 1.9 landfalls per year. From the above one can conclude that the number of US hurricane landfalls tend to be overestimated in the seasonal forecasts for recent years. This is the result of the exceptional recent behavior of hurricane landfalls: The United States has not experienced a landfalling major hurricane since 2005, the longest period on record (since reliable records began in 1878). It is unclear whether this arises from (very good) luck or from changes in the environmental factors affecting the motion of hurricanes.

As one would expect, hurricane activity is correlated to insurance losses. This is true for the observed number of hurricanes *(Figure 8)*, the NTC metric (not shown) and even more so for the ACE metric *(Figure 8)*. Nevertheless, there is no significant correlation between the May-June and August forecasts and losses *(Table 4)*. The August ACE forecast issued by TSR and insured US losses have a rank correlation coefficient of 0.39 *(Figure 9)*. This value although not statistically significant implies a considerable association with losses.

Figure 7. Number of US hurricane landfalls predicted by TSR (grey shade) and observed values. The uncertainty range is two standard deviations of the error of past real-time forecasts.

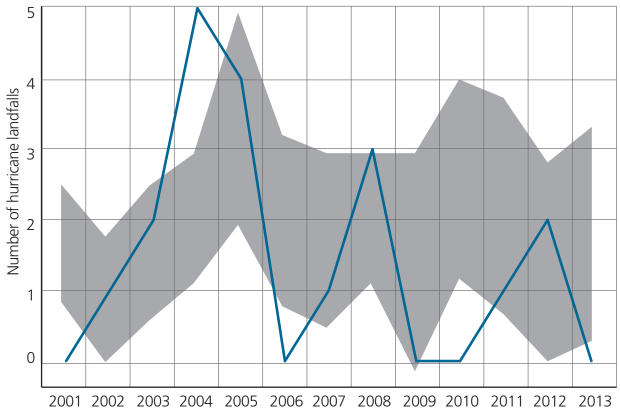


Figure 8. Observed number of basin hurricanes (left) and ACE (right) versus insurance losses. The corresponding years are shown as well (e.g. number "05" on the plot indicates the 2005 hurricane season). Vertical dash lines indicate the 2001-2013 average of the number of hurricanes (left) and ACE (right).

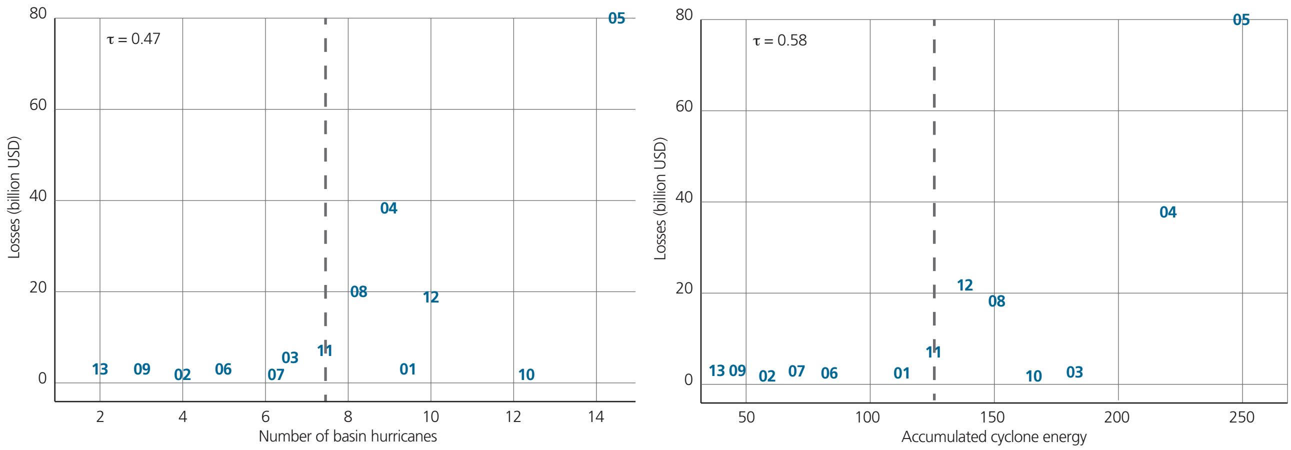
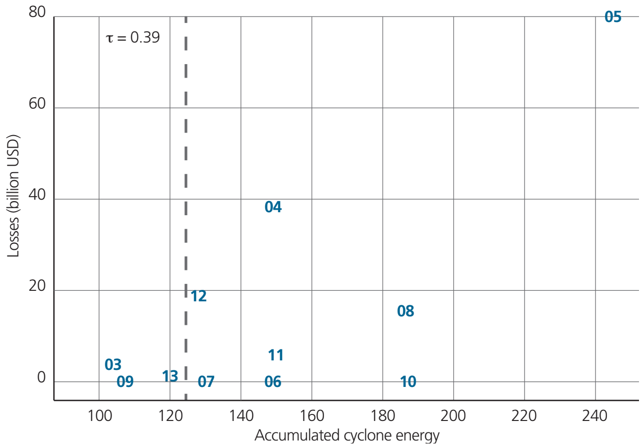


Table 4. Kendall's tau correlation coefficient between observed/forecast hurricane activity and insurance losses. Bold numbers in green color indicate significant correlation at the 95% level of confidence.

	ACE	NTC	n.o. hurricanes
Observations	**0.58**	**0.44**	**0.47**
CSU May-June	-	-0.14	-0.21
CPC May-June	-0.12	-	-0.16
TSR May-June	-0.17	-	-0.05
CSU August	-	0.12	0.15
CPC August	0.14	-	0.2
TSR August	0.39	-	0.17

Figure 9. TSR August predictions of ACE versus insurance losses. Vertical dash line indicates the 2001-2013 average ACE.



A (Re)insurance Perspective

Significant forecast skill from August or July onwards does not allow integration of the additional knowledge into reinsurance transactions since the last major renewal date for the US wind season is July 1st (before the forecast signal becomes very skillful). The current June forecasts are a little better than climatology, but not robust enough to integrate into a decision-making process.

However, what might a significantly skillful earlier forecast mean for the (re)insurance industry? There are two problems with forecasting from an underwriting perspective: how much weight to give it (addressed above) and what to do with the information. From a business perspective, it would not make sense to rely on a forecast when deciding how much reinsurance or retrocession to buy, and not only because the existing accuracy is low. The current state of forecasting does not correlate well with potential loss. (Re)insurance is a long-term business and as such takes the view that a balance sheet should be protected in most reasonable circumstances. Capital requirements are regulated by rating agencies and the insurance commissioners of each state. These stakeholders will continue to define the minimum capital requirements, and it is inconceivable that these minima would be reset on the basis of a forecast.

Insurers take strategic decisions to structure and purchase reinsurance to protect earnings and balance sheets and these decisions are not likely to significantly influenced by the short-term (weekly/monthly) risk factors. Improved forecasting is therefore unlikely to affect the fundamental buying behaviour of insurance companies. Balance sheets cannot be put at risk because of a forecast. However, improved forecasting skill could potentially have an impact on the 'non-core' reinsurance purchases such as 3rd/4th event covers, top & drop or aggregate deals. Demand for these ancillary covers could increase as a result of a forecast from both a frequency and severity perspective .

Another potential impact is on the Business Plan rather than the Financial Plan (e.g. claims adjustment resources for an insurer). The insurer may choose to have more adjusters in place in advance of a poor season and the reinsurer might take a more conservative view of potential loadings for loss adjustment expenses, additional living expenses, demand surge, etc. if the forecast was for a high frequency season.

"Marginal decision" making in (re)insurance can also be informed using late season forecasting. A "marginal decision" is one where the underwriting conclusion to write/not write a deal is, on balance, inconclusive according to all the usual metrics used. In these cases, a forecast could tip the scale in favour of a particular choice. For example in 2005, the conditions in May/June suggested a year analogous to those with moderate to severe Texas landfalling hurricanes such as those which occurred in 1961, 1967 and 1983.

Are there other opportunities that could arise if forecasts were significantly more skillful? Perhaps the best we could hope for would be the use of forecasting in the development of post-July parametric products or a 'live hurricane trading' platform that takes into account the latest probabilities of landfalls. Trading opportunities could arise from 'dealing the signal', whether that is the Bermuda High or sea surface temperatures. Parametric products could be developed that are triggered by a risk factor-weighted combination of the following:

- Sea surface temperature
- North Atlantic Oscillation/Bermuda High
- El Niño conditions
- Steering current (jet-stream)/ Loop current position
- Sahara sand or volcanic particulates.

4 This contrasts with the Medium Term/Warm Sea surface temperature view which is dependent on a belief about the current state of the climate

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Conclusions and outlook

Seasonal forecasts of hurricane activity issued by three prominent forecasting groups have been compared with observations. Our analysis supports the conclusion that forecasts issued in early August, early July and early June represent an improvement over using a recent or long-term average of the hurricane activity. This is not the case for the TSR forecast issued at the beginning of early April. Looking at the forecast errors since 2001, no significant improvement is visible for any of the examined forecasting schemes. All examined forecasts are strongly correlated to each other. This is not surprising since some important environmental factors affecting hurricane activity (such as the El Niño and sea surface temperature in parts of the North Atlantic) are common predictors in all three forecasting schemes. Nevertheless, significant differences in the methodologies do exist and this is reflected in the results too. For example, the TSR August forecast of basin ACE shows some correlation with insured losses whereas the other forecasts do not. Forecasts of hurricane landfalls are even more difficult and one of the groups in question (CPC) does not provide them. The groups that perform such forecasts have tended to over-predict the number of landfalls in the last 13 seasons. In general, seasonal forecasts do provide useful information on the upcoming hurricane activity as of June each year. However, hurricane activity exhibits such strong variability that the actual outcome each year often deviates strongly even from the relatively skillful August forecasts.

From a (re)insurance perspective, improved forecasting is unlikely to affect fundamental buying behaviour. Even with much improved forecasting for severity, given the motivation for the purchase of cover and the constraints on the amount of capital that must be held by an insurance company outlined above, it is unlikely to influence the minimum amount of cover bought. However, a forecast of an active season could increase the demand for ancillary products. From a reinsurance underwriting perspective, improved forecasting may influence marginal choices. Forecasting skill would need to improve significantly to lead to the development of new products.

Despite some unsuccessful years in hurricane forecasting all stakeholders will keep looking at the seasonal forecasts with great interest in the future. The 2013 forecast was one of the worse ever. This could be the result of simply bad luck or the result of important predictors being missed. Various research groups are currently investigating this topic. In that sense, the lack of skill for the 2013 season provides an opportunity to advance our knowledge around hurricanes and their prediction.

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References

CPC. 2001. “Background information: The North Atlantic hurricane season.” Atlantic hurricane outlook. (http://www.cpc.ncep.noaa.gov/products/outlooks/hurricane2001/May/background_information.html).

Elsner, James B. and Thomas H. Jagger. 2006. “Prediction models for annual U.S. hurricane counts.” *Journal of Climate.*

Goldenberg, Stanley B., Christopher W. Landsea, Alberto M. Mestas-Nunez, and William M. Gray. 2001. “The recent increase in Atlantic hurricane activity: causes and implications.” *Science.*

Gray, William M. 1984. “Atlantic seasonal hurricane frequency. Part II: Forecasting its variability.” *Monthly Weather Review.*

Gray, William M., Christopher W. Landsea, Paul W. M. Jr, and Kenneth J. Berry. 1994. “Predicting Atlantic basin seasonal tropical cyclone activity by 1 June.” *Weather and Forecasting.*

Klotzbach, Philip J. and William M. Gray. 2009. “Twenty-five years of Atlantic basin seasonal hurricane forecasts (1984–2008).” *Geophysical Research Letters.*

LaRow, Timothy E., Lydia Stefanova, Dong-Wook Shin, and Steven Cocke. 2010. “Seasonal Atlantic tropical cyclone hindcasting/forecasting using two sea surface temperature datasets.” *Geophysical Research Letters.*

Pielke, Roger A. J. and Christopher N. Landsea. 1999. “La Niña, El Niño and Atlantic hurricane damages in the United States.” *Bulletin of the American Meteorological Society.*

Saunders, Mark A. and Adam S. Lea. 2005. “Seasonal prediction of hurricane activity reaching the coast of the United States.” *Nature.*

Simmons, David and Mark Saunders. 2005. “ReMetrics Review: Using hurricane forecasts to adjust peril model loss probabilities.” Tropical Storm Risk. Retrieved 2013 (https://www.tropicalstormrisk.com/docs/ReMetricsTSR-Oct2005.pdf).

Tang, Brian and Kerry Emanuel. 2010. “Midlevel ventilation’s constraint on tropical cyclone intensity.” *Journal of the Atmospheric Sciences.*

Vecchi, Gabriel A., Ming Zhao, Hui Wang, Gabriele Villarini, Anthony Rosati, Arun Kumar, Isaac M. Held, and Richard Gudgel. 2011. “Statistical–Dynamical predictions of seasonal North Atlantic hurricane activity.” *Monthly Weather Review.*

Vitart, Frederic. 2006. “Seasonal forecasting of tropical storm frequency using a multi-model ensemble.” *Quarterly Journal of the Royal Meteorological Society.*

Wang, Hui, Jae-Kyung E. Schemm, Arun Kumar, Wanqiu Wang, Lindsey Long, Gerald D. B. Muthuvel Chelliah, and Peitao Peng. 2009. “A statistical forecast model for Atlantic seasonal hurricane activity based on the NCEP dynamical seasonal forecast.” *Journal of Climate.*

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