North Atlantic seasonal hurricane prediction:

Underlying science and an evaluation of statistical models

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Abstract

Statistically-based seasonal hurricane outlooks for the North Atlantic were initiated by Colorado State University (CSU) in 1984, and have been issued every year since that time by CSU. The National Oceanic and Atmospheric Administration (NOAA) Climate Prediction Center and the UK-based Tropical Storm Risk (TSR) have the next longest records (1998-present) of continuous outlooks. This chapter describes how these three forecasts have evolved with time, and documents the approaches, the environmental fields, and the lead times which underpin the models' operation. Some of the environmental parameters used in early seasonal outlooks are no longer employed, but new predictive fields have been found which appear to be more important for seasonal hurricane prediction. An assessment is made of the deterministic skill of the seasonal hurricane outlooks issued in real-time by CSU, NOAA, and TSR between 2003 and 2014. All methods show moderate-to-good skill for early August outlooks (prior to the most active portion of the hurricane season), low-to-moderate skill for outlooks issued in early June, and lesser skill for outlooks issued in early April. Overall, the TSR model has the most skillful predictions of Accumulated Cyclone Energy (ACE), while NOAA has the best named storm predictions issued in early August.

1. Introduction

Tropical cyclones (TC) are severe weather events that form in many parts of the tropics, and impact continents, including North America, Asia, Australia, and Africa. The damage caused by tropical cyclones can be catastrophic, and will only continue to increase as coastal developments expand and populations grow [Mendelsohn et al., 2012; Peduzzi et al., 2012]. Improving our ability to predict seasonal tropical cyclone activity is one way to mitigate this increase in damage [DeMaria et al. 2014].

The tropical climate system influences atmospheric dynamics and sea surface temperature (SST) anomaly patterns in all TC basins. Therefore, the climate system affects the strength of the hurricane seasons throughout the world. Because of this climate influence, some level of seasonal predictive skill is being achieved for most hurricane basins.

This chapter focuses on seasonal predictions of North Atlantic hurricane activity. The North Atlantic hurricane season lasts for six months from 1 June to 30 November. The season has a well-defined 3-month peak of August-September-October (ASO), during which 77% of all named storms, 84% of all hurricanes, and 93% of all major hurricanes have formed (1950-2014 data).

Atlantic hurricane seasons feature large year-to-year and decade-to-decade fluctuations in strength, primarily in response to differing amounts of activity during ASO. Figure 1 shows the set of conducive conditions within the MDR during ASO that produce a more active Atlantic hurricane season. Opposite conditions suppress hurricane formation and intensification in the MDR and produce a less active season. Gray [1984a, b], Bell and Chelliah [2006] and others have linked active and inactive hurricane seasons to seasonal fluctuations in oceanic and atmospheric conditions during ASO within the Atlantic hurricane Main Development Region (MDR, yellow box in Figure 1), which spans the tropical North Atlantic Ocean and Caribbean Sea [Goldenberg et al., 2001]. Such fluctuations often have strong climate links and involve a set of inter-related parameters, including SSTs, trade wind strength, vertical wind shear, atmospheric stability and the strength of the west African monsoon. Therefore, above-normal and below-normal Atlantic hurricane seasons are typically not random occurrences. Instead, they often reflect a strong climate influence over a set of atmospheric and oceanic conditions within the MDR, which then collectively determines the overall strength of the hurricane season.

The seasonal hurricane outlooks are designed primarily to predict oceanic and atmospheric conditions within the MDR during ASO. Two large-scale climate phenomena, the El Niño/Southern Oscillation (ENSO) and the Atlantic Multi-Decadal Oscillation (AMO) account for much of the coherent variability observed across the MDR in the atmosphere and ocean on both inter-annual and multi-decadal time scales [Goldenberg et al., 2001; Bell and Chelliah, 2006]. This high degree of control exerted by the tropical climate system on Atlantic hurricane activity provides the underlying scientific basis for making seasonal Atlantic hurricane outlooks. Studies have well-established that by monitoring, understanding, and predicting these climate patterns and their associated regional circulation features, it is often possible to confidently predict the nature of the upcoming hurricane season.

One benefit of issuing seasonal outlooks is to anticipate the likelihood of extreme events. While weak tropical storms can form in marginally favorable environments, a set of very conducive conditions (Fig. 1) is required to produce powerful hurricanes and an exceptionally active season. Seasonal prediction models typically forecast an aggregate measure of overall seasonal activity such as the Accumulated Cyclone Energy (ACE) index [Bell et al., 2000]. The ACE index measures the combined intensity and duration of all named storms during the season, and it is therefore a measure of the overall strength of the hurricane season. ACE correlates strongly with major hurricanes (Category 3-5 on the Saffir-Simpson wind scale). For example, in seasons classified as below-normal (<66 ACE units) by NOAA since 1966 (when daily geostationary satellite data became available), an average of 0.9 major hurricanes formed, compared with 3.9 major hurricanes in above-normal seasons (>111 ACE units). This 4:1 ratio is especially important when one considers that major hurricanes cause approximately 80-85% of TC-related damage on an annual basis [Pielke Jr. et al., 2008].

This chapter evaluates the three longest-lived outlooks for North Atlantic hurricane activity. In order of longevity, these outlooks have been issued by: Colorado State University (CSU), the National Oceanic and Atmospheric Administration (NOAA) and Tropical Storm Risk (TSR). CSU started disseminating operational seasonal hurricane outlooks in 1984. NOAA's seasonal outlooks started in August 1998, and TSR began publishing seasonal outlooks in December 1998. Successful predictions of Atlantic basin seasonal hurricane activity are now also being made by dynamical models, such as those issued by the European Centre for Medium Range Weather Forecasts (ECMWF) [Vitart and Stockdale, 2001] and the UK Met Office [Camp et al., 2015].

Building upon Klotzbach [2007] this chapter provides an updated review of statistically-based seasonal hurricane outlooks for the North Atlantic basin, including an assessment of their skill. Section 2.1 summarizes the initial prediction scheme used by CSU in 1984. Section 2.2 discusses the development of CSU's seasonal hurricane outlooks since 1984. Section 2.3 describes the evolution of NOAA's outlooks since their original issuance in 1998. Section 2.4 provides a discussion of prediction development from TSR since 1999. In section 2.5 the real-time outlook skill of the three forecast models is evaluated and compared for the period 2003-2014. Potential future improvements to the statistical models are discussed in section 2.6. Section 3 concludes the chapter.

2. Statistically-Based Seasonal Hurricane Outlook Models

The reason why the North Atlantic was chosen in 1984 for the first statistically-based seasonal tropical cyclone outlook was the greater year-to-year variability in TC activity present in this basin compared to the Northeast Pacific or Northwest Pacific basins (Gray, personal communication). Based on 1986-2005 data, the coefficient of variation (the ratio of the standard deviation to the mean) is nearly twice as large for the Atlantic as for the Northeast Pacific and about three times as large for the Atlantic as for the Northwest Pacific [Klotzbach 2007].

2.1 Early Research and Outlooks

Before 1984 there was little way of knowing how active an upcoming hurricane season would be. CSU issued the first statistically-based seasonal hurricane outlooks for the North Atlantic basin in 1984 [Gray, 1984b]. Since then, the CSU outlooks have evolved and are currently available at http://tropical.atmos.colostate.edu. Early outlooks for the Atlantic basin were issued in June and updated in August. These outlooks utilized current and predicted strengths and phases of two large-scale climate phenomena: ENSO and the Quasi-Biennial Oscillation (QBO) [Gray, 1984a], along with forecasts of Caribbean basin sea level pressure (SLP). Figure 2 shows the six stations utilized to estimate Caribbean basin SLP anomalies. When an El Niño event was present, the predicted level of Atlantic hurricane activity was reduced, while both ENSO-neutral and La Niña events were treated equally. If the QBO was in its easterly phase at 30-hPa, or if the 30-hPa winds were increasing from the east, the predicted level of hurricane activity was reduced. If the QBO was in its westerly phase or the 30-hPa winds were increasing from the west, a stronger hurricane season was predicted. If SLP in the Caribbean basin was below average a stronger hurricane season was predicted, and if SLP in this region was above average a weaker hurricane season was predicted. This initial model showed considerable hindcast skill. The correlation between hindcast and observed named storms (tropical storms and hurricanes combined) was 0.82 for the period 1950-1982 (Fig. 3), and the correlation for hurricanes alone was 0.77.

2.2 CSU Model Development: 1984-Present

CSU's outlooks have undergone significant evolution since their original release. CSU began releasing early December predictions in 1990, while continuing to issue both June and August outlooks. Gray et al. [1992; 1993; 1994] detail the CSU prediction models used in the early 1990s. Figure 4 displays the predictors utilized in the early 1990s for their early August prediction scheme.

While all of CSU's seasonal outlooks still retain an ENSO component, other predictors have been added or removed over the years. For example, the models used in the early 1990s included new predictors that were closely related to West African rainfall. As discussed by Landsea and Gray [1992], when rainfall in the Western Sahel is enhanced during June-July, Atlantic hurricane seasons tends to be more active. A stronger West African monsoon is associated with stronger and better defined easterly waves, weaker vertical wind shear, and warmer sea surface temperatures (SSTs) in the MDR, all of which favor more frequent and more intense tropical storms and hurricanes [Bell and Chelliah 2006]. In addition, Landsea and Gray [1992] found a significant relationship between Gulf of Guinea rainfall during August-November and Atlantic hurricanes the following year. This relationship was a key predictor in CSU's original early December prediction model. Figure 5 displays the tracks of major hurricanes during the ten wettest vs. ten driest years for the Gulf of Guinea region during the period from 1949 to 1989.

In the mid-1990s the development of the NCEP/NCAR Reanalysis products [Kistler et al., 2001] led to a transition from station-based predictors to grid-based predictors. In addition, the failure of previously-used predictors, such as the QBO [Camargo and Sobel, 2010] and direct African rainfall measurements [Klotzbach and

Gray, 2004] caused CSU to investigate other climate predictors. These failures also illustrated the challenges of making seasonal outlooks in an inherently non-stationary climate system.

While original forecast models were constructed using limited data (e.g., 1950-1980), longer periods of hindcast data are now available. In addition, with the development of the 20th Century Reanalysis [Compo et al., 2011], a full three-dimensional realization of the atmosphere is now available back to 1851. Obviously, as one goes back in time, there is increased uncertainty both in atmospheric parameters and levels of hurricane activity. However, being able to evaluate predictor skill over 100+ years of prior data helps to avoid some of the pitfalls associated with predictor screening [DelSole and Shukla 2009].

CSU discontinued its December outlooks following the 2011 hurricane season due to a lack of real-time predictive skill. The project currently issues outlooks in April, June, July, and August [Klotzbach, 2014]. Figure 6 displays the three predictors currently used in CSU's early August outlook.

As indicated, the CSU outlooks now utilize the low-level wind flow across the Caribbean Sea as an important predictor. Using the ERA-Interim Reanalysis [Dee et al., 2011], July Caribbean trade winds correlate with post-1 August ACE at 0.78. This predictor had previously been noted by Saunders and Lea [2008] to explain a significant amount of variability of Atlantic TC activity. Indeed TSR has used the predicted speed of the August-September Caribbean trade winds as one of its two main predictors for seasonal hurricane activity since 2001.

This trade-wind predictor is important because it is associated with a set of conditions which together influence Atlantic hurricane activity. For example, reduced trade wind strength over the Caribbean Sea implies higher than normal pressure in the eastern tropical Pacific which is typically associated with La Niña conditions. Weaker trade winds are also typically associated with warmer than normal conditions in the tropical Atlantic and Caribbean Sea, along with an expanded Atlantic Warm Pool [Wang and Lee, 2007]. A larger warm pool generates a more conducive dynamic and thermodynamic environment for TC genesis and intensification.

Another predictor currently used by CSU is the SST anomaly in the northeastern subtropical Atlantic. The Atlantic tends to be more active when SSTs in this region are warmer than normal prior to the peak of the hurricane season [Klotzbach, 2011; Klotzbach, 2014], likely because these warm anomalies tend to get advected into the Atlantic by the peak of the hurricane season [Smirnov and Vimont, 2012]. Additionally, warmer temperatures in this region are typically associated with weaker trade winds and a more conducive configuration of the African Easterly Jet (AEJ) during the peak months of the hurricane season.

2.3 NOAA Model Development: 1998-Present

NOAA's seasonal hurricane outlooks for the North Atlantic basin are an official product of the Climate Prediction Center and are made in collaboration with NOAA's National Hurricane Center and Hurricane Research Division. NOAA began issuing seasonal hurricane outlooks in August 1998. The outlooks, beginning with May 1999, are archived at: www.cpc.ncep.noaa.gov/products/outlooks/hurricane-archive.shtml. These outlooks provide a general guide to the expected strength of the upcoming hurricane season. They are not a seasonal hurricane landfall outlook, and do not imply levels of activity for any particular location. NOAA's initial seasonal hurricane outlook is issued in late- May and is then updated in early August.

For the outlooks issued from August 1998-May 2000, NOAA only indicated the most likely season strength. Since August 2000, the outlooks have indicated the probabilities for the three season classifications: above-, near-, and below-normal, as defined at www.cpc.nce.noaa.gov/products/outlooks/background_information.shtml#NOAADEF. Since August 2001 the outlooks have also include probabilistic statements for the likely ranges of named storms, hurricanes, major hurricanes, and ACE. However, there was flexibility during 2001-2002 in what was referred to as a "likely" range. Since May 2003, the "likely" ranges of activity have been specified with an estimated 70% probability of occurrence.

NOAA's seasonal hurricane outlooks reflect predictions of the combined impacts of three climate factors: ENSO [Gray, 1984; Goldenberg and Shapiro, 1996], the AMO [Gray et al., 1996; Landsea et al., 1999], and the tropical multi-decadal signal (TMS) [Bell and Chelliah, 2006]. The TMS is the leading multi-decadal mode of tropical convective variability, and it captures the observed link between multi-decadal fluctuations in Atlantic SSTs (i.e. the AMO), the West African monsoon system [Hastenrath 1990; Gray, 1990; Landsea and Gray, 1992; Landsea et al., 1992; Goldenberg and Shapiro, 1996] and Amazon Basin rainfall [Chen et al., 2001; Chu et al., 1994]. Together, these climate factors produce the inter-related set of atmospheric and oceanic conditions typically associated with both seasonal and multi-decadal fluctuations in Atlantic hurricane activity (Fig. 1).

Three types of forecast tools provide guidance for the outlooks [Bell and Blake, 2015]. These include statistical tools, a hybrid statistical/dynamical ensemble forecast technique based on the NOAA Climate Forecast System (CFS) Version-2 (T-128), and purely dynamical model ensemble forecasts from the CFS high-resolution (T-382) model, the ECMWF, and the EUROpean Seasonal to Inter-annual Prediction (EUROSIP) model (Figure 7). The updated outlook issued in August also incorporates predictive information such as anomalous early season activity, and atmospheric and oceanic anomalies that may have developed which are not related to the dominant climate predictors.

One statistical prediction technique utilizes linear multiple regression equations to first establish the historical relationship between seasonal activity and the combined effects of the above climate factors. Forecasts of these climate factors are then input into the regression equations to predict the upcoming seasonal activity. In practice, the regression results for each prediction parameter are assembled into a look-up table [Bell and Blake, 2015], allowing forecasters to quickly assess a likely range of activity given uncertainties in the climate prediction itself. A second statistical technique uses climate-based analogues, which provide the forecaster with the observed ranges of activity in past seasons having similar climate conditions to those currently being predicted.

The hybrid statistical/dynamical technique [Wang et al., 2009] uses regression equations to relate historical CFS-V2 model forecasts of anomalous seasonal Atlantic SSTs and vertical wind shear to the observed seasonal hurricane activity in that year. The results are used to quantify the observed ranges of activity during past seasons having model predictions similar to the present.

One purely dynamical forecast tool in use since 2009 is the set of ensemble forecasts obtained from the CFS high-resolution model [Schemm and Long, 2009]. This tool provides guidance to the seasonal hurricane outlooks in three main ways. First, it aids in the prediction of the climate predictors themselves. Second, it aids in predicting the strength of the regional circulation anomalies associated with those climate predictors, which is especially important when there are competing climate factors or when there is an expectation for a significant evolution in those climate factors (such as ENSO) as the season progresses. Third, the model provides independent, bias-corrected predictions of seasonal activity based purely on model-generated hurricane tracks. Along similar lines, in 2010 the outlooks also began taking into account ensemble dynamical model predictions obtained from the ECMWF and the EUROSIP.

To arrive at the final seasonal hurricane outlook, all predicted ranges obtained from the various prediction tools are first assembled. Consensus guidance outlook ranges are then obtained by averaging separately, over all the prediction tools, the lower bounds and the upper bounds of the predicted ranges. The individual team forecasters then use this guidance to make predictions for the likely ranges of activity (~70% confidence) for each prediction parameter. The final Atlantic outlook reflects a consensus of these individual forecaster predictions.

2.4 TSR Model Development: 1999-Present

Tropical Storm Risk (TSR), based at University College London in the UK, has issued public outlooks for seasonal TC activity in the North Atlantic since December 1998. The TSR venture developed from a UK government-supported initiative called TSUNAMI, which ran from 1998 to 2000, and whose aim was to assist the competitiveness of the UK insurance industry.

TSR predicts basin-wide TC activity (namely numbers of storms of different strengths and the ACE index), U.S. landfalling TC activity, and Caribbean Lesser Antilles landfalling TC activity. Outlooks are issued in deterministic and tercile probabilistic form. The TSR prediction models are statistical in nature, but are underpinned by predictors that have sound physical links to contemporaneous TC activity. TSR issues seasonal outlooks in early December, April, June, July and August. All historical TSR seasonal TC outlooks are available online at www.tropicalstormrisk.com/forecasts.html thereby allowing assessments to be made of the TSR real-time forecast skill. However, during the period from December 1998 through 2001 the TSR seasonal forecast models and their lead times of issue were evolving. For a consistent assessment of TSR prediction skill at set lead times, it is recommended to use only outlooks starting with the 2002 hurricane season. TSR also provides within its seasonal outlooks, the hindcast precision of each outlook parameter assessed over a prior 35-year period.

The TSR seasonal hurricane forecast model is sophisticated for a statistical model. The model divides the North Atlantic hurricane basin into three regions: (1) the tropical North Atlantic; (2) the Caribbean Sea and Gulf of Mexico; (3) the remainder of the North Atlantic outside regions (1) and (2). TSR employs separate outlook models for each of the three regions before summing the regional hurricane outlooks to obtain an overall North Atlantic hurricane outlook.

For regions (1) and (2) the model pools different environmental fields involving predictions of August-September SST anomalies and July-September trade wind speed to select the environmental field or combination of two fields which gives the highest replicated real-time skill for individual predictands (number of tropical storms, number of hurricanes, number of major hurricanes, and ACE index) over the prior 10-year period. The nature of this process means that the details of the seasonal forecast model can vary subtly: (1) between individual predictands at the same lead time for a given year; (2) with lead time for the same predictand during the same year; and (3) from year-to-year for the same predictand at the same lead time. Separate forecast models are employed to predict: (1) July-September trade wind speed; (2) August-September SST anomalies for different regions in the tropical North Atlantic and Caribbean Sea; and (3) August-September SST anomalies for different Nino regions [Lloyd-Hughes et al., 2004]. Finally bias corrections are employed for each predictand based on the performance of that predictand over the prior 10 years.

Two environmental fields stand out amongst the fields which the TSR model pools in making its selection described above. These fields are: (1) Predicted speed of the trade winds for July-August-September for the region 7.5°-17.5°N, 100°W-30°W. The trade winds blow westward across the tropical Atlantic and Caribbean Sea and influence cyclonic vorticity and vertical wind shear over the MDR; and (2) Predicted SST anomaly for August-September for the region 10°-20°N, 60°W-20°W between West Africa and the Caribbean, which includes the central and eastern MDR where many hurricanes develop during August and September. Waters here provide heat and moisture to help power the development of storms within the MDR. The nature of these two environmental fields and their anomalies, which are linked to active hurricane seasons, is shown in Figure 8. Further information on the TSR outlooks for North Atlantic TC activity and its underpinning methodology is described in Lea and Saunders [2004; 2006], Saunders [2006], and Saunders and Lea [2008].

TSR outlooks for US landfalling TC activity issued between December and July employ a historical thinning factor between 'tropical' North Atlantic activity and U.S. landfalling activity. The TSR outlook for U.S. landfalling activity issued in early August employs the persistence of July steering winds [Saunders and Lea, 2005]. These winds either favor or hinder evolving hurricanes from reaching U.S. shores during August and September. This model correctly anticipates whether U.S. hurricane losses are above-median or below-median in ~75% of the years between 1950 and 2013. For the U.S. ACE index, the TSR prediction skill increases from 3% (prior December) to 29% (early August) for the period 1980-2013.

2.5 Assessment of Seasonal Hurricane Outlook Skill: 2003-2014

An assessment and inter-comparison of the real-time forecast skill of the CSU, NOAA and TSR hurricane outlooks was performed for the 12-year period 2003-2014. This period is chosen because the forecast methodologies employed by each group have remained relatively stable over this period (see sections 2.2, 2.3 and 2.4), and because these outlooks are available and archived on their public websites.

The deterministic August outlooks for the four main measures of hurricane activity; ACE, major hurricane numbers, hurricane numbers, and named storm numbers, that were issued by each forecast group during 2003-2014 are shown in Figure 9. Since NOAA does not issue deterministic outlook values, but instead issues an outlook range having a 70% probability of occurrence, the mid-point of their outlook range is used as a proxy for their deterministic value.

Notable forecast successes are evident (e.g. 2005, 2010 and 2014) as well as forecast failures (e.g. 2007 and 2013). The 12-year period includes the most active hurricane season on record (2005) as well as the quietest hurricane season since the early 1980s (2013). Thus, although the assessment period is relatively short it provides a reasonable test of outlook performance.

The skill assessment and comparison is made separately for the four main measures of hurricane activity, and separately for the three outlook issue times of early April, early June (at the start of the official hurricane season) and early August (just prior to the main part of the hurricane season). It should be noted that only CSU and TSR issue outlooks in early April and that the NOAA outlook issued in late May is treated here as an early June outlook.

The assessment examines two measures of deterministic outlook skill. The first is the Spearman rank correlation (r_{rank}), which is a robust and resistant alternative to the Pearson product-moment correlation coefficient [Wilks, 2006]. The second skill measure is the mean square skill score (MSSS), defined as the percentage reduction in mean square error of the outlooks compared to outlooks made with a climatological mean. MSSS is the skill metric recommended by the World Meteorological Organization

(WMO) for verification of deterministic seasonal outlooks [WMO, 2002; also see Déqué, 2003]. The MSSS is calculated here with respect to two different climatologies: a fixed 1951-2000 mean and a rolling prior 10-year mean. A prior 10-year mean is used, instead of the prior 5-year mean as recommended by the WMO [WMO, 2008], because the 10-year mean is found to be a tougher benchmark to beat for all measures of hurricane activity.

Figures 10 and 11 display the real-time skill of the seasonal hurricane outlooks computed for the different lead times and activity measures. Figure 10 shows the skill using the Spearman rank correlation (r_{rank}), and Figure 11 shows the skill using the mean square skill score (MSSS). The findings from these two skill assessments are similar. For all models, the August outlooks are by far the most skillful, and the April outlooks are the least skillful. Overall, the TSR model is the most skillful predictor of the ACE index and is also the most skillful pre-season and early-season predictor for hurricane numbers. The NOAA model has the best August prediction for named storm numbers.

Benchmark skill values were then obtained by identifying the best performing statistical outlook model for each measure of hurricane activity based on the MSSS scores. The benchmark MSSS skill values for ACE, major hurricane numbers and hurricane numbers are 10-20% for early April outlooks, 20-30% for early June outlooks, and 40-60% for early August outlooks. For named storm numbers, the benchmark MSSS values are 0-40% for early April outlooks, 20-60% for early June outlooks, and then increase to 60-80% for early August outlooks. These are the largest skill scores of all predicted parameters. The lower value in these ranges correspond to the MSSS calculated with respect to the prior 10-year mean (dashed lines) and the larger value corresponds to the MSSS calculated with respect to the 1951-2000 mean.

The benchmark MSSS values show that the best performing statistical seasonal model offers skill for all measures of hurricane activity and that this skill extends out to early April. This skill may be described as moderate-to-good for early August outlooks, low-to-moderate for early June outlooks, and low for early April outlooks.

2.6 Future of Atlantic Basin Seasonal Hurricane Prediction

Although seasonal Atlantic hurricane outlooks are showing skill from early April, it is likely that there are untapped sources of seasonal predictability which can further enhance the predictive skill. These untapped sources of predictability may come, for example, from the identification of significant additional forcing factor(s) in years when ENSO is neutral and/or from further developments in dynamical modeling. We anticipate that as model resolution, data assimilation techniques and model physics continue to improve, the utility of dynamical models for seasonal outlooks will continue to increase.

However, as this chapter focuses on statistical predictions, two areas of research related to future developments in statistical modeling are addressed. One promising area for further statistical model development is the ability to generate forecast models built over longer periods of data. In general, models built over long periods of data should prove to be more reliable in the future. The 20th Century Reanalysis developed by the Earth System Research Laboratory (ESRL) [Compo et al., 2011] as well as the ERA-20C project from the ECMWF [Stickler et al., 2014] provide gridded datasets since the start of the 20th century. These datasets ingest surface data and then use an Ensemble Kalman filter (in the case of the 20th Century Reanalysis) and 4D variational data assimilation (in the case of the ERA-20C) to arrive at estimates of upper-air fields. The ECMWF is currently intensively involved in data rescue efforts from pibals and weather balloon data from the 1920s and 1930s in preparation for a fully-coupled three-dimensional realization of the atmosphere dating back to 1900. There is obviously increased uncertainty as one heads back in time, but these datasets have proved and will likely continue to prove useful in better estimating the stability of relationships between predictors and Atlantic hurricane activity.

Another area that has helped with improving the accuracy of statistically-based seasonal outlooks has been the reanalysis of the Atlantic basin hurricane database (HURDAT2) [Landsea and Franklin, 2013]. As is the case with large-scale fields, there is increased uncertainty in observed hurricane activity earlier in the record. This uncertainty becomes especially large prior to the mid-1960s when no geostationary satellite data was available. The reanalysis has attempted to reconstruct historical hurricane tracks back to 1851 using historical records from newspapers, ship logs, and other sources. This project is currently in the middle of the 20th century and has likely provided more accurate estimates of historical ACE. Vecchi and Knutson [2008, 2011] have also provided an estimate of named storms and hurricanes; respectively, that were likely missed prior to 1965 through examination of ship traffic across the Atlantic basin. A similar adjusted ACE metric would be useful for continued improvement of statistically-based models of seasonal hurricane activity.

3. Conclusions

This chapter has described how statistically-based Atlantic basin seasonal hurricane outlooks have developed since their inception in 1984. The first seasonal outlooks were issued by CSU, and were based on the phase of ENSO, the phase of the QBO, and Caribbean sea level pressure anomalies. The CSU model has evolved and now employs a variety of predictors derived from the latest global reanalysis products. In the late 1990s statistically-based seasonal hurricane outlooks were initiated by two other groups: NOAA and TSR. The NOAA model is statistical-dynamical in form and utilizes statistical techniques analyzing the state of the AMO and ENSO, combined hybrid statistical/dynamical techniques, and dynamical model output. The TSR model is sophisticated for a statistical model but primarily utilizes two predictors: 1) predicted tropical Atlantic sea surface temperatures and 2) predicted low-level trade wind flow across the tropical Atlantic and Caribbean Sea.

All three prediction models (CSU, NOAA and TSR) show significant real-time skill for the 2003-2014 period, with the August outlooks being by far the most accurate. Overall, NOAA's August outlooks show the most skill in predicting named storm numbers. The TSR model shows the most skill in predicting ACE, and also has the highest pre-season and early-season skill in predicting hurricane numbers.

The benchmark MSSS values show that the best performing statistical seasonal model offers skill for all measures of hurricane activity and that this skill extends out to early April. This skill may be described as moderate-to-good for early August outlooks, low-to-moderate for early June outlooks, and low for early April outlooks. It is likely that untapped sources of seasonal hurricane predictability remain to be discovered, and it is possible for statistical models to gain modest improvements upon the seasonal real-time outlook skills documented herein.

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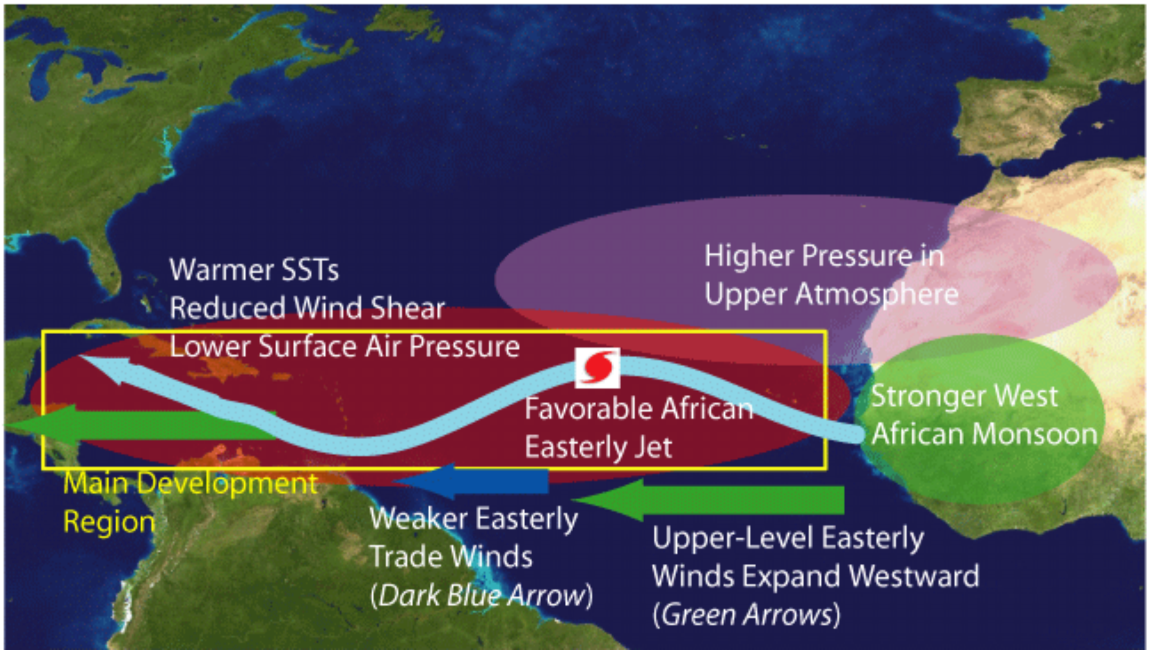

Figure 1: Schematic of atmospheric and oceanic anomalies during August-October associated with active Atlantic hurricane seasons and decades. Adapted from Bell and Chelliah [2006].

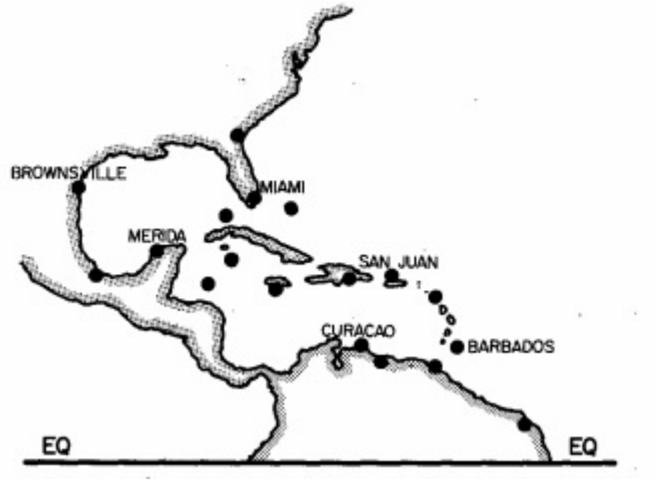

Figure 2: Locations of six stations used to estimate Caribbean basin sea level pressure anomalies in the original CSU outlook. Figure taken from Gray [1984b].

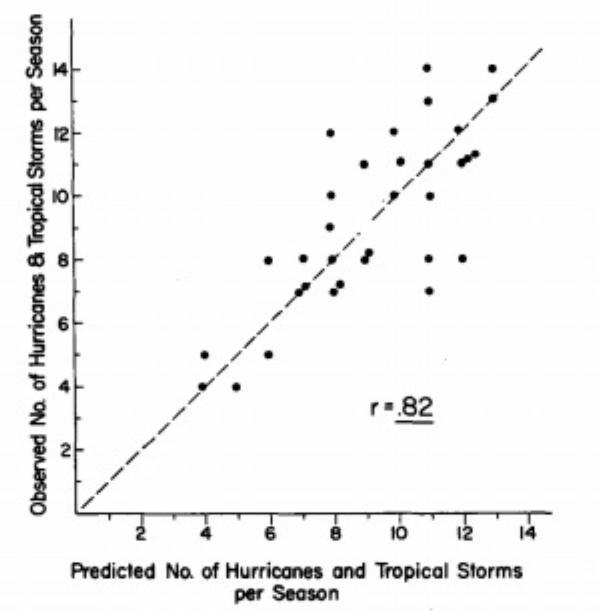

Figure 3: Hindcast skill based on the period 1950-1982 of the original early August outlook issued by CSU. The correlation (r) between the hindcast and observed number of hurricanes and tropical storms combined is 0.82. Figure taken from Gray [1984b].

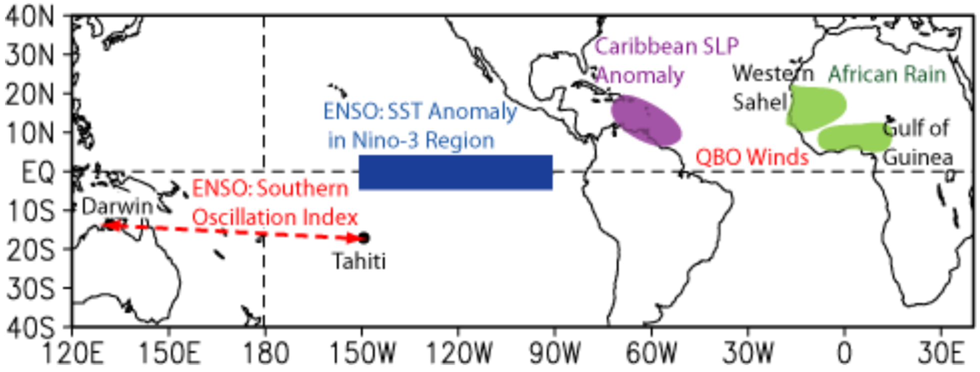

Figure 4: Predictors utilized by CSU in the early 1990s for their August seasonal outlook. Labels not mentioned in the text include: 1) the Southern Oscillation Index, which is used to monitor ENSO and is a measure of the anomalous sea-level pressure difference between Darwin, Australia and Tahiti, and 2) the Niño-3 region, which is an important area of the tropical Pacific used to monitor ENSO. Figure adapted from Gray et al. [1993].

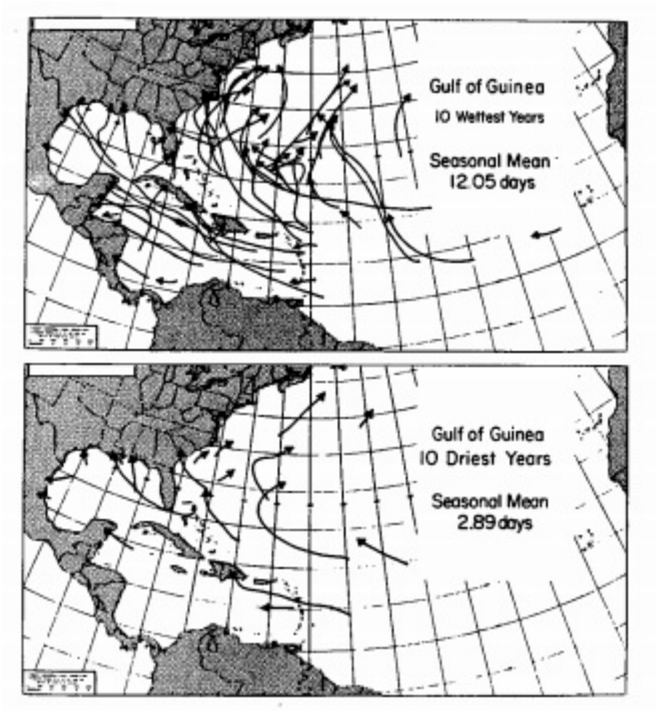

Figure 5: Tracks of major hurricanes in the year following the ten wettest August-November periods in the Gulf of Guinea (top panel) and the ten driest August-November periods from 1949-1989. This finding was why the previous August-November Gulf of Guinea rainfall was utilized in the initial early December outlook scheme issued by CSU. Figure taken from Gray et al. [1992].

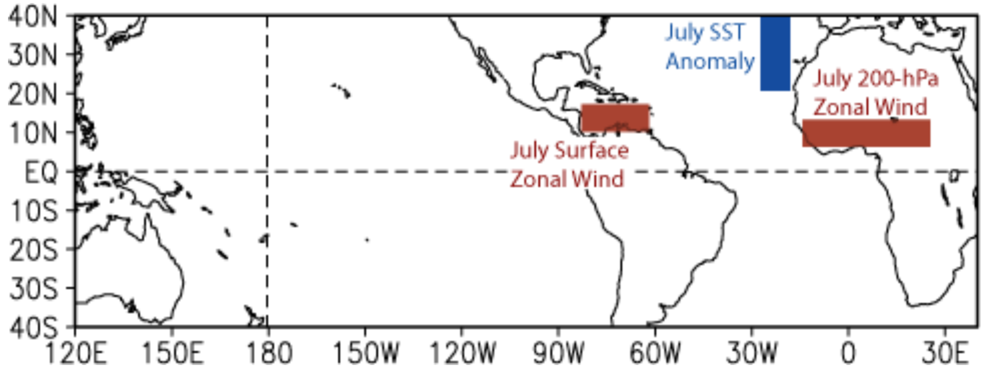

Figure 6: Location of predictors for CSU outlooks currently being issued in early August.

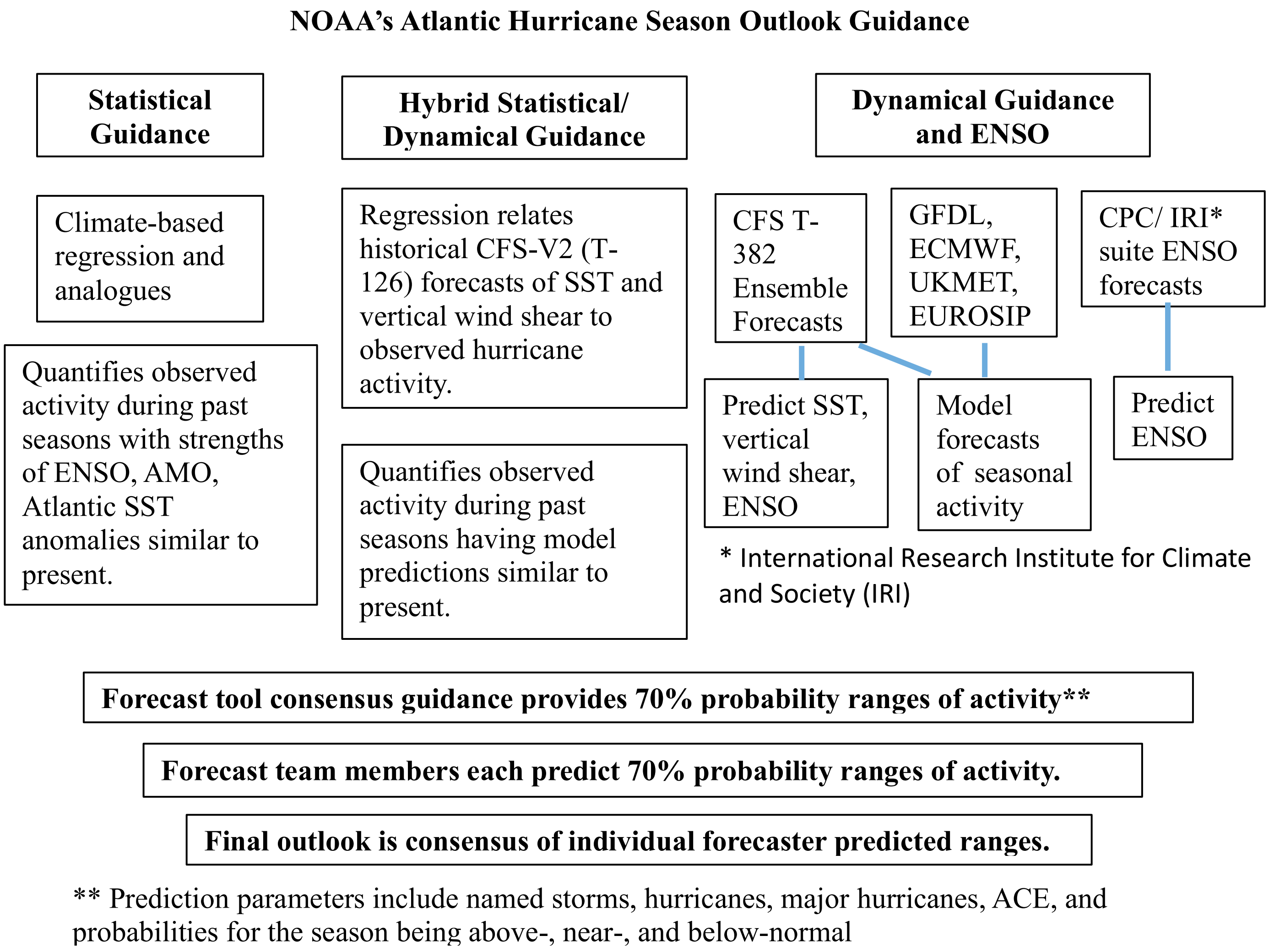

Figure 7: Schematic illustrating the tools which provide guidance for NOAA's Atlantic hurricane season outlooks.

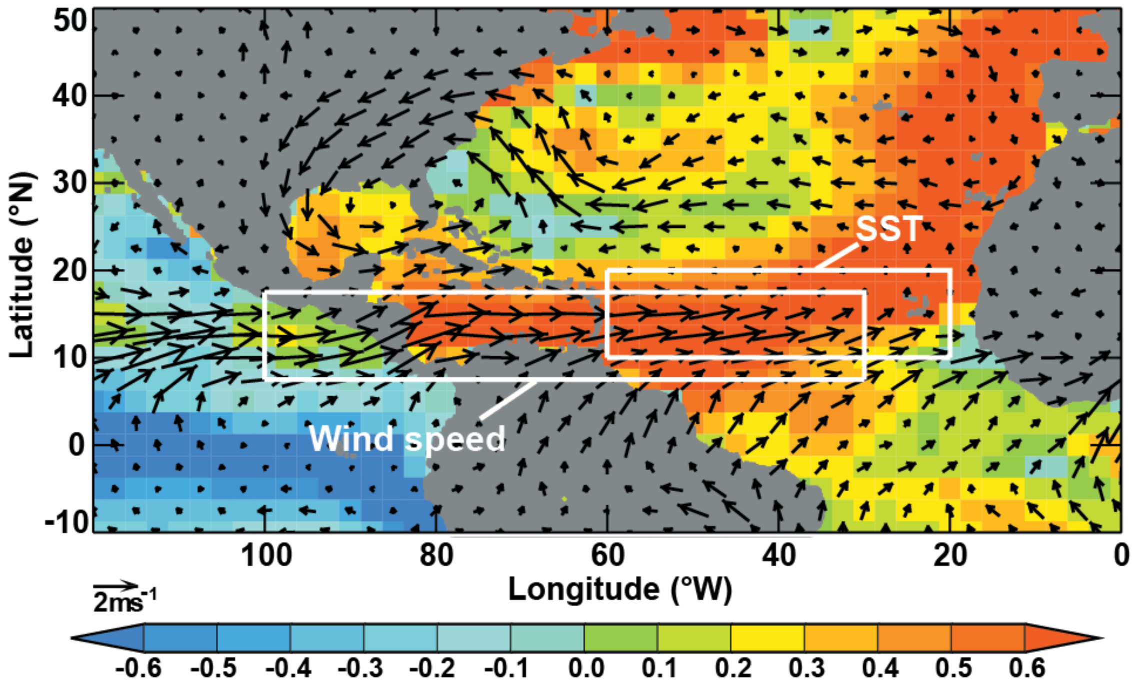

Figure 8: Nature of the TSR statistical model for replicating North Atlantic seasonal hurricane activity. The figure displays the two August-September environmental field areas that the TSR model employs most often in producing a seasonal hurricane outlook. The figure also displays the anomalies in August-September SST (color coded in °C) and 925 hPa wind (arrowed) linked to active Atlantic hurricane years. Figure taken from Saunders and Lea [2008].

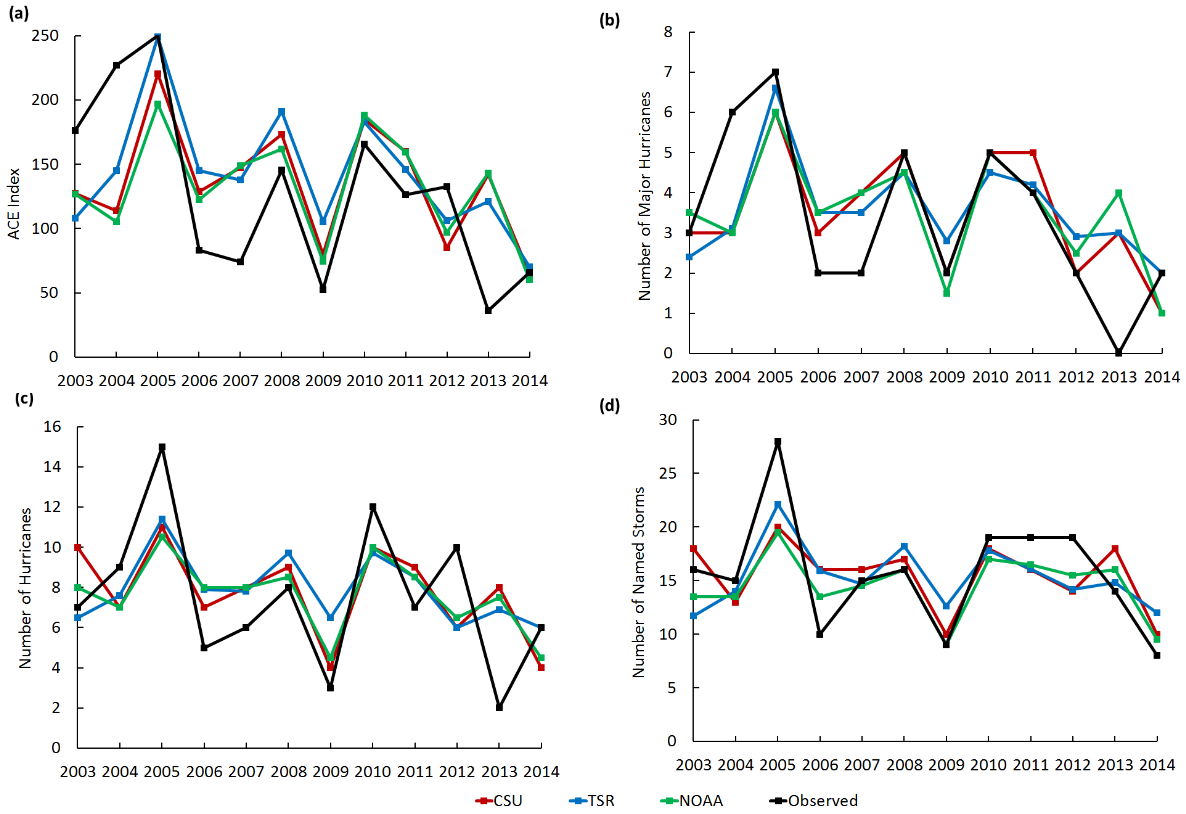

Figure 9: Time series comparing the seasonal outlook values issued in early August 2003-2014 by CSU, TSR and NOAA with observed values. The comparison is made for (a) ACE, (b) Major hurricane numbers, (c) Hurricane numbers, and (d) Named storm numbers.

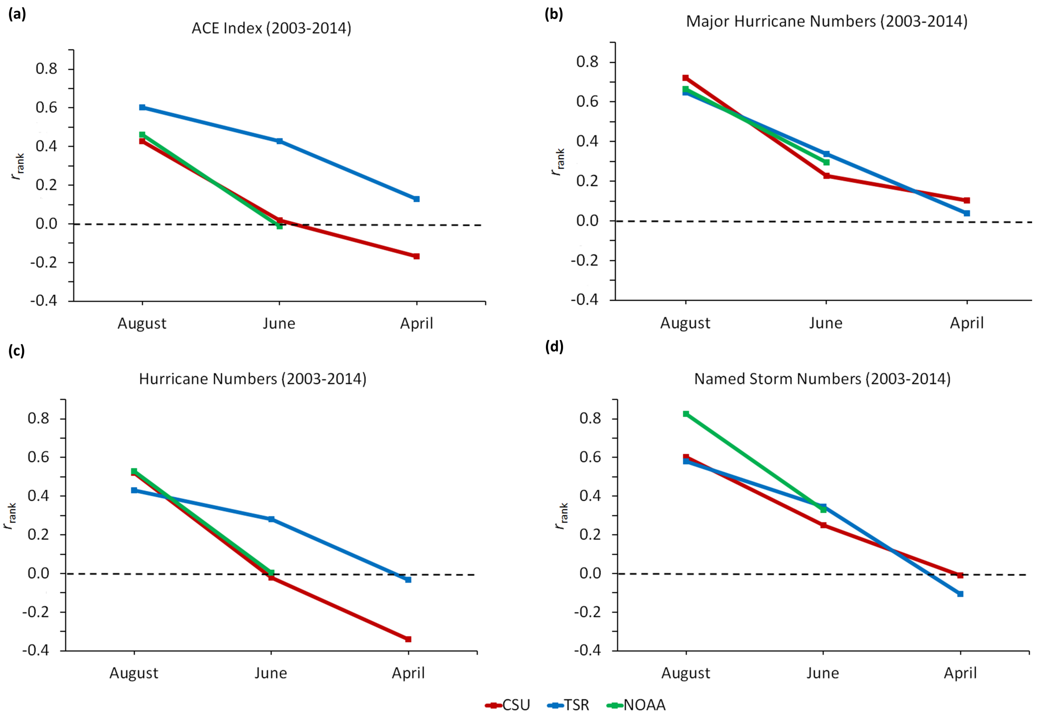

Figure 10: Skill of North Atlantic seasonal hurricane outlooks from 2003-2014 assessed using the Spearman rank correlation (r_{rank}) between the forecast and observed values. The assessment is made for (a) ACE, (b) Major hurricane numbers, (c) Hurricane numbers, and (d) Named storm numbers. In each case the r_{rank} values are computed for CSU, TSR and NOAA seasonal outlooks issued at lead times of early August, early June and early April.

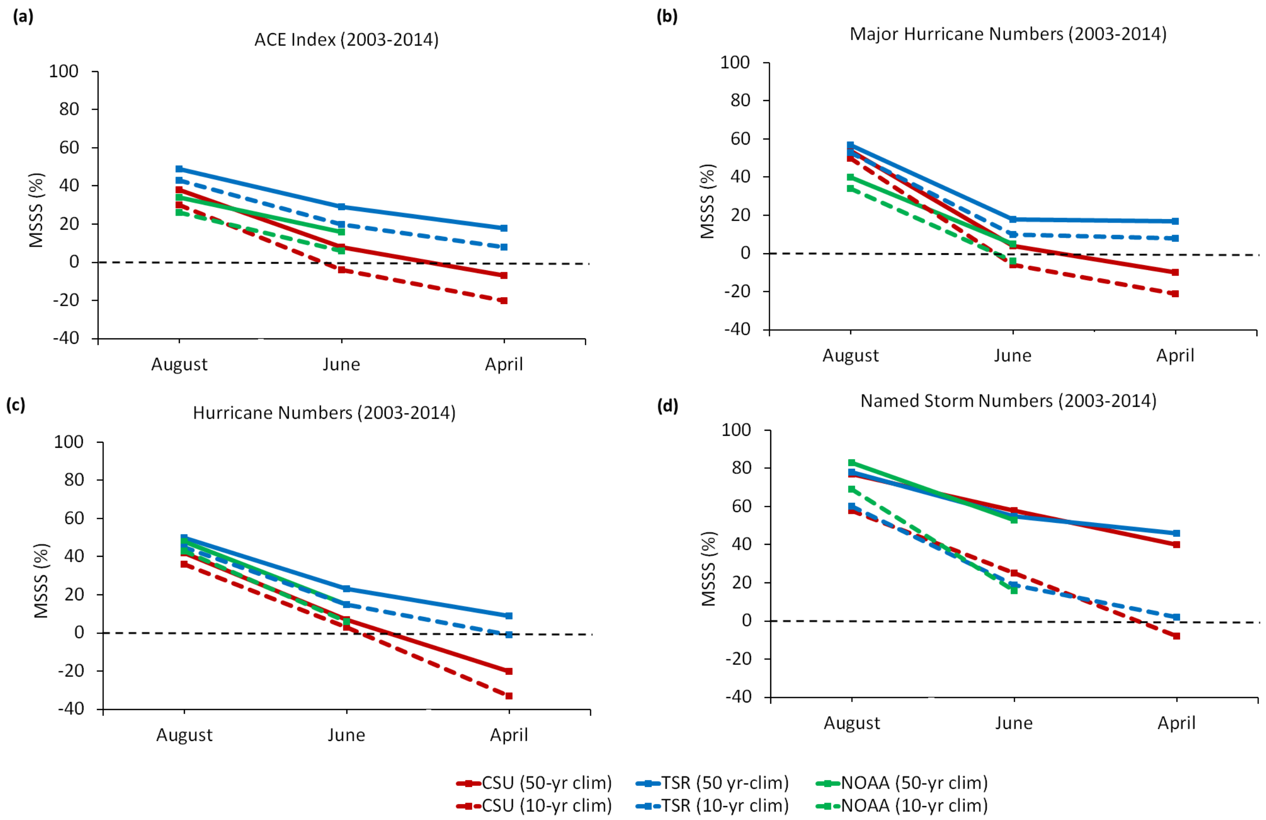

Figure 11: Skill of North Atlantic seasonal hurricane outlooks 2003-2014 assessed using the mean square skill score (MSSS) and displayed in the same format as Figure 10. The MSSS skill assessment is made with two different climatology forecasts: a fixed 1951-2000 mean and a rolling prior 10-year mean.