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Key Points:
- A statistical/dynamical model is developed to forecast seasonal Atlantic hurricane activity that demonstrates skill on ~40 years of data
- The ECMWF SEAS5 forecast system is used to forecast input parameters to Colorado State University's early August statistical scheme
- A combination of statistical and statistical/dynamical models yields improved hurricane forecasts compared to either model separately

Supporting Information:
- Supporting Information S1

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A Statistical/Dynamical Model for North Atlantic Seasonal Hurricane Prediction

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Abstract Colorado State University (CSU) has been issuing seasonal hurricane forecasts since 1984, with statistical modeling techniques primarily underpinning these outlooks. CSU has recently begun issuing statistical/dynamical forecasts, using the SEAS5 forecast system from the European Centre for Medium-Range Weather Forecasts to forecast the three predictors that currently comprise CSU's early August statistical forecast model. SEAS5 shows skill at forecasting all three of these July predictors from an initialization as early as 1 March. The SEAS5 model forecasts for the three parameters are then regressed against seasonal accumulated cyclone energy. The model has a cross-validated correlation skill of $r = 0.60$ with accumulated cyclone energy for a 1 March initialization, improving to $r = 0.67$ for a 1 June initialization over the period from 1982–2019. The combination of the statistical/dynamical model with the currently existing statistical models shows improved skill over either model individually for the April, June, and July outlooks.

Plain Language Summary The Tropical Meteorology Project at Colorado State University (CSU), founded by the late Dr. William Gray, has been issuing seasonal Atlantic basin hurricane forecasts since 1984. These forecasts have primarily used statistical modeling approaches that take historical relationships between Atlantic hurricane activity and various climate features, such as El Niño-Southern Oscillation and tropical Atlantic sea surface temperatures. In this study, we use the European Centre for Medium-Range Weather Forecasts System 5 (SEAS5) model to forecast the three large-scale predictors that currently comprise the early August statistical hurricane forecast model used by CSU. SEAS5 shows skill at forecasting each of these predictors during July from initialization as early as 1 March. The forecasted predictors from the dynamical model are then used to make a statistical forecast of accumulated cyclone energy—an integrated metric accounting for intensity and duration of hurricane activity. The model shows skill at predicting accumulated cyclone energy at all lead times, with improving skill as the lead time decreases. The combination of CSU's currently existing statistical models and the statistical/dynamical models detailed in this manuscript shows improved skill over either model individually for the early April, June, and July outlooks, with the most notable improvement in early April.

1. Introduction

The Tropical Meteorology Project at Colorado State University (CSU), founded by the late Dr. William Gray, has been issuing North Atlantic (hereafter Atlantic) basin seasonal hurricane forecasts operationally since 1984 (Gray, 1984). The predictors underpinning these forecasts have changed over the years, but the primary input tool driving the CSU forecasts has been a statistically-based scheme using historical relationships between large-scale climate parameters such as El Niño-Southern Oscillation, tropical and subtropical Atlantic sea surface temperatures (SSTs), and trade wind strength across the Caribbean versus Atlantic hurricane activity (e.g., Gray et al., 1992, 1993, 1994; Klotzbach, 2007; Klotzbach et al., 2017). These forecasts issued in early June and August have shown skill relative to various no-skill metrics, including a long-term climatology and the previous 5-year and 10-year means (Klotzbach et al., 2017; Klotzbach & Gray, 2009). Though these forecasts have shown skill in hindcast mode at an April lead time, they have yet to show long-term real-time forecast skill since the April forecasts began operationally in 1995 (Klotzbach et al., 2017). CSU recently updated all of its seasonal forecast models to utilize the newly released fifth generation reanalysis from the European Centre for Medium Range Weather Forecasts (ECMWF; ERA5) reanalysis (Hersbach et al., 2020) along with the National Oceanic and Atmospheric Administration (NOAA) Optimum Interpolation SST Version 2 data set (Reynolds et al., 2007). The new April model

(Klotzbach et al., 2020a), for example, demonstrates cross-validated hindcast skill ($r = 0.64$) at hindcasting accumulated cyclone energy (ACE; Bell et al., 2000) over the period from 1982–2019.

As an alternative approach to statistical modeling, several groups are now using statistical/dynamical forecasts to predict tropical cyclone (TC) activity in the Atlantic and other basins (Klotzbach et al., 2019). As the skill of climate models has improved in recent years, their ability to forecast large-scale parameters critical for Atlantic hurricane activity has also improved (e.g., Vecchi et al., 2011). For example, NOAA currently uses forecasts of large-scale conditions from the North American Multimodel Ensemble (Harnos et al., 2019), as well as its individual components such as the Climate Forecast System Version 2 (Finan et al., 2018) and the Geophysical Fluid Dynamics Laboratory Forecast version Low Ocean Resolution (FLOR; Vecchi et al., 2014) and high-resolution Forecast version Low Ocean Resolution (Murakami et al., 2015, 2016) models to predict Atlantic hurricane activity as part of the suite of products that it uses to issue seasonal hurricane forecasts.

Monthly seasonal forecasts from several climate modeling groups are now made available by the C3S, enabling the issuance of statistical/dynamical model forecasts in real time. Here, we examine the ability of the System 5 (SEAS5) forecast system from ECMWF (Johnson et al., 2019) to forecast the inputs to the current early August statistical forecast model used by CSU (Klotzbach et al., 2020d). We focus on the 1 March, 1 May, and 1 June initialization dates for the SEAS5 forecast system, since these are the model runs that would be available for real-time guidance for the CSU seasonal hurricane forecasts issued in early April, early June, and early July, respectively.

The remainder of this paper discusses the development of the statistical/dynamical forecasts. Section 2 describes the data sources and statistical techniques used, while section 3 outlines and provides physical justification for the inputs to the early August statistical model. Section 4 describes the statistical/dynamical forecast model development and evaluation. Section 5 provides some ideas for future work and concludes the manuscript.

2. Data and Statistical Techniques

TC statistics are calculated from the Atlantic basin hurricane database (HURDAT2; Landsea & Franklin, 2013). This data set currently includes 6-hourly synoptic positions and intensities of TCs from 1851–2019. In this study, we classify seasonal hurricane activity using ACE, which is defined to be the sum of the squares of each 6-hourly time period where a tropical (or subtropical) cyclone has maximum sustained winds of 34 kt or greater (e.g., a named storm) (Bell et al., 2000) divided by 10,000.

Large-scale atmospheric fields are computed from ERA5. This reanalysis is available at 30 km horizontal resolution with 137 vertical levels. The current data set extends from 1979 up to the present, with a planned backward extension to 1950 set to be released later in 2020. Sea surface temperature observations are taken from the high-resolution (0.25°) NOAA Optimum Interpolation SST Version 2 data set, available from September 1981 to the present.

The dynamical model outputs are taken from the ECMWF SEAS5 product, which is the current operational seasonal forecast system run by ECMWF. The system consists of initial conditions used to estimate the initial state of the climate and a global coupled ocean-atmosphere general circulation model to calculate the evolution of the ocean, atmosphere, and sea ice. The ocean component is Nucleus for European Modeling of the Ocean v3.4 (horizontal resolution ~25 km; Madec et al., 2016), initialized using Ocean ReAnalysis System 5 and OCEAN5 real-time (Zuo et al., 2019), while the atmosphere component is Integrated Forecast System Cycle 43r1 (horizontal resolution ~36 km), initialized using ERA-Interim (hindcasts) (Dee et al., 2011) and ECMWF operational analyses (forecasts). Here, we use the ensemble mean, which is constructed using 25 ensemble members for the hindcast period (1981–2016) and 51 ensemble members for the forecast period (from 2017 up to the present). More details on the dynamical modeling system are provided in supporting information Table S1.

While the SEAS5 model output is initially produced at 36 km horizontal resolution with 91 vertical levels, we download the data from the Climate Data Store at 1° resolution, which is the common standard for seasonal forecasts on the Climate Data Store. The model is run on the 1st of each month, and forecasts extend out to 7 months (e.g., a 1 March initialization would forecast conditions through September). The SEAS5 hindcasts

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run from 1981–2016, with operational forecasts available since that time. Since CSU's statistical forecasts start in 1982 given the initiation of the NOAA OISSTv2 data set in September 1981, we evaluate the skill of SEAS5 from 1982 to 2019 in this analysis.

We use both the Pearson correlation coefficient and the Spearman rank correlation coefficient to evaluate the skill of the individual predictors as well as the model suite at predicting ACE for the 1982–2019 period. In the remainder of this document, Pearson correlations are denoted in regular text, with Spearman rank correlations immediately following in parentheses. Statistical significance is evaluated at the 5% level using a two-tailed Student's *t* test and treating each hurricane season as an independent observation, since the autocorrelation between one year's ACE and the next year's ACE is low (e.g., $r = 0.30$ [$r_{rank} = 0.28$] from 1982–2019). We use a cross-validated approach (Efron & Tibshirani, 1993), that is, we leave out the year being hindcast when reporting model skill at predicting ACE. This approach to reporting skill for statistical modeling of hurricane activity has been advocated in several prior studies including Blake and Gray (2004), Elsner and Schmertmann (1994), and Klotzbach (2014).

3. Current Operational CSU Early August Statistical Hurricane Forecast Model

Figure 1 displays the current operational CSU early August statistical hurricane forecast model (Klotzbach et al., 2020d) including a map of the predictor locations as well as a time series comparing observed post-1 August ACE with cross-validated hindcast post-1 August ACE. The exact latitude and longitude boundaries of the individual predictors that comprise the model as well as the individual predictor's correlations with ACE from 1982–2019 are provided in Table S2. All of the current generation of CSU's statistical models issued at various lead times are derived using linear regression, with predictors selected based on how much variance they explained over the 1982–2019 period. More details on the individual CSU statistical seasonal hurricane forecast schemes issued in early April, June, July, and August are available in their respective 2020 seasonal hurricane forecasts (Klotzbach et al., 2020a, 2020b, 2020c, 2020d).

The three-predictor early August model correlates with post-1 August ACE at 0.81 (0.82), indicating that ~65% of the variance in post-1 August ACE can be explained by this model. Hereafter, all references to "model" refer to the early August statistical hurricane forecast model unless otherwise noted. We now briefly discuss the physical hypothesis for how each predictor likely impacts Atlantic hurricane activity and examine how the predictors correlate with large-scale fields/indices during the peak months of the Atlantic hurricane season from August–October, when 86% of Atlantic ACE was generated using the current NOAA 1981–2010 climate averaging period. More detailed discussion of the physical linkages is provided in Klotzbach et al. (2020d). Note that the region used to delineate Predictor 1 for the statistical/dynamical model is slightly larger than what was used in Klotzbach et al. (2020d) for the statistical model (e.g., 10–17.5°N, 85–60°W vs. 10–20°N, 90–40°W). We find a similar correlation using the larger region and calculating averages over larger regions in SEAS5 reduces potential issues with model biases. All statistics quoted for the remainder of the manuscript use the larger Predictor 1 region.

3.1. Predictor 1: July 10 m Zonal Wind (10–20°N, 90–40°W)

Trade winds over the Caribbean and the central tropical Atlantic have been used as a predictor in seasonal Atlantic hurricane forecasts for nearly 20 years (e.g., Klotzbach et al., 2019; Saunders & Lea, 2008; Saunders & Rockett, 2001; Saunders et al., 2020). The strength of August–September trade winds averaged over the Caribbean and tropical Atlantic was the most robust predictor for Atlantic hurricanes during the period from 1878–2012 (Saunders et al., 2017). Anomalously weak trade winds are associated with a larger-than-normal Atlantic Warm Pool (Wang & Lee, 2007), likely due to a wind-evaporation-SST feedback mechanism whereby weaker winds cause less evaporation resulting in increased SST. Also, weaker July trade winds are associated with below-average vertical wind shear (Saunders & Lea, 2008), both during July and during August–October. The correlation between July 10 m zonal wind (denoted hereafter as U) and August–October 200 minus 850 hPa zonal wind shear in the Caribbean and central tropical Atlantic (10–20 N, 90–40°W) from 1982–2019 is −0.80 (−0.77).

3.2. Predictor 2: July Sea Surface Temperature (20–40°N, 35–15°W)

Anomalously warm subtropical eastern Atlantic sea surface temperatures are associated with a weaker-than-normal Azores high and reduced trade wind strength in the eastern tropical Atlantic. These

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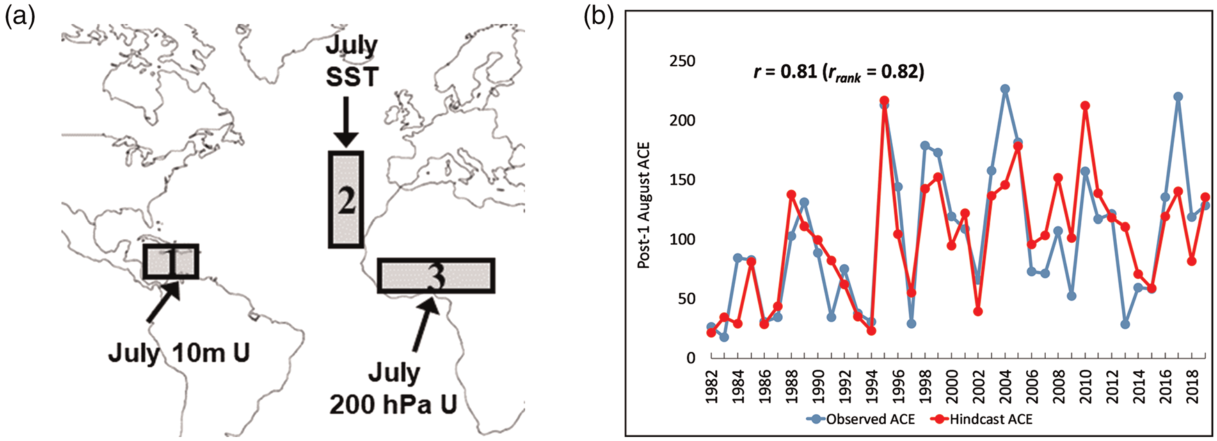

Figure 1. Summary of the early August Atlantic statistical seasonal hurricane prediction model currently used by CSU. (a) Map of the locations of the three predictors in the statistical model. (b) Time series displaying observed and cross-validated hindcasts of post-1 August ACE hindcasts by the statistical hurricane model from 1982–2019.

anomalously weak trade winds promote anomalous warming of the tropical Atlantic via a wind-evaporation-SST feedback mechanism, favoring a positive phase of the Atlantic Meridional Mode (Kossin & Vimont, 2007) during the peak of the hurricane season from August–October. The correlation between this predictor and the August–October-averaged value of the sea surface temperature component of the Atlantic Meridional Mode in August–October, based on data from 1982–2019, is 0.70 (0.67). CSU has used a similar predictor in several previous iterations of its seasonal hurricane forecast models (e.g., Klotzbach, 2007, 2011).

3.3. Predictor 3: July 200 hPa Zonal Wind (5–15°N, 0° to 40°E)

Anomalous easterlies at upper levels over tropical West Africa are associated with a stronger West African monsoon and a TC-favorable configuration of the tropical easterly jet (Bell & Chelliah, 2006). Due to the baroclinic response associated with convection in the tropics, anomalous westerlies occur at low levels over West Africa and the eastern tropical Atlantic, providing a more conducive environment for TC formation due to increased cyclonic vorticity along the southern periphery of the African easterly jet (Bell & Chelliah, 2006; Klotzbach & Gray, 2003; Russell et al., 2017). Anomalous easterlies at upper levels over West Africa are also linked to more conducive shear conditions across the Caribbean and tropical Atlantic. The correlation between this predictor and August–October 200 minus 850 hPa zonal wind shear in the Caribbean and central tropical Atlantic (10–20°N, 90–40°W) from 1982–2019 is 0.65 (0.68).

4. Statistical/Dynamical Model Forecast Development and Evaluation

Figure 2 summarizes the skill of SEAS5 at predicting the individual predictors comprising the statistical hurricane model at three different forecast times: 1 March, 1 May, and 1 June. All parameters have been standardized based on their 1982–2019 averages and standard deviations. These lead times will be referred to as March, May, and June through the remainder of the text. As was noted earlier in the manuscript, these lead times are what is used for the early April, early June, and early July seasonal forecasts issued by CSU. The model forecasts for all three parameters correlate significantly with observed values from a March initialization date, with the model skill for each predictor generally improving as the forecast lead time decreases. The predictor with the most notable improvement in correlation skill is for July 10 m U in the Caribbean/central tropical Atlantic, with SEAS5 explaining over 60% of the variance by a June initialization date. Some of this increase in skill is likely due to the relationship between the trade wind predictor with ENSO and the associated improvement in ENSO forecast skill by SEAS5 as the boreal spring predictability barrier passes (Chen et al., 2020).

Given that SEAS5 is able to explain significant amounts of variability for each predictor comprising the early August statistical hurricane forecast by a March initialization date, we next investigate if these three

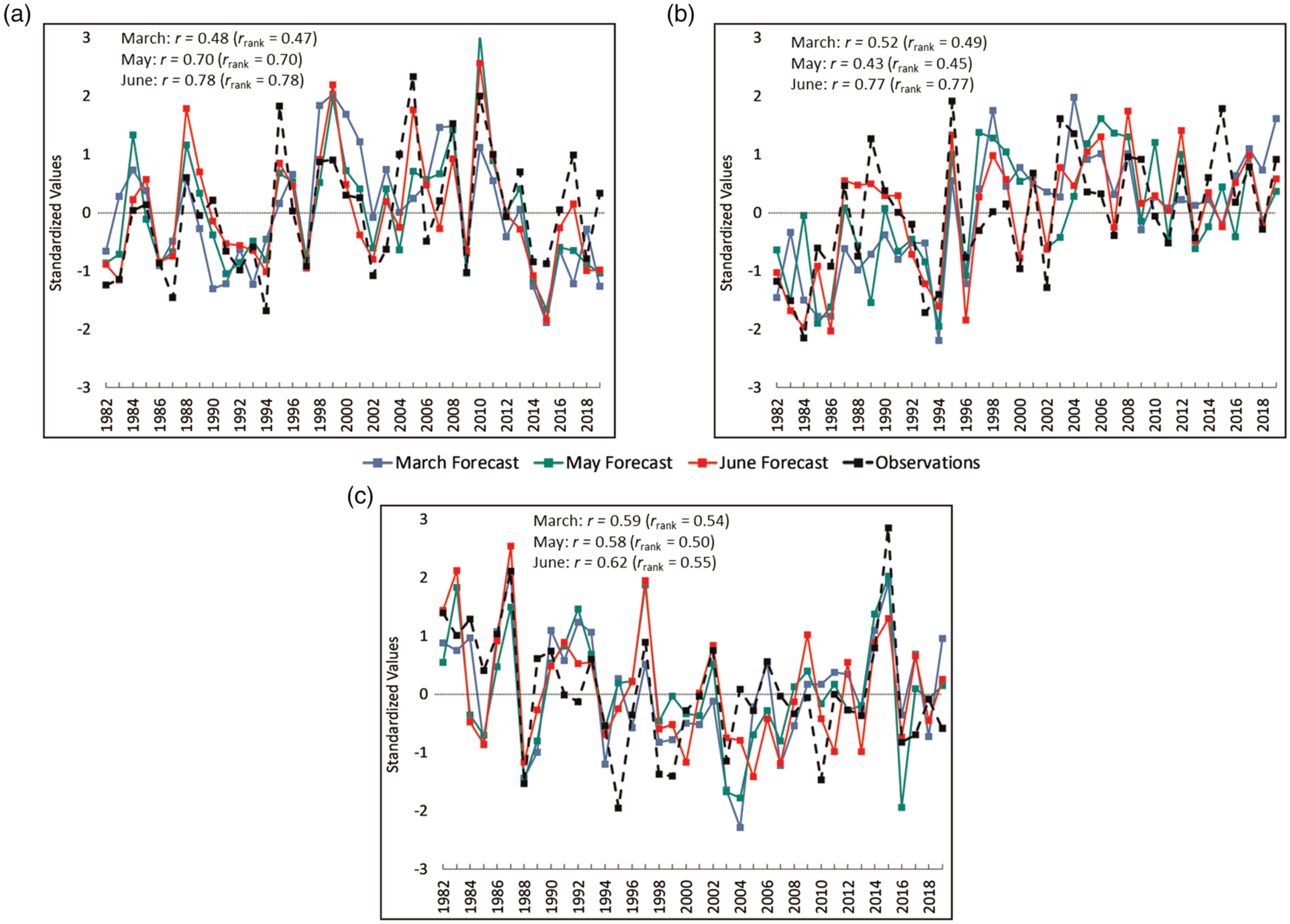

Figure 2. SEAS5 forecasts of the three individual predictors comprising the early August statistical model compared with observations. All parameters have been standardized based on a 1982–2019 base period. (a) SEAS5 hindcasts/forecasts of July 10 m U in the Caribbean and central tropical Atlantic. (b) SEAS5 hindcasts/forecasts of July SST in the subtropical eastern Atlantic. (c) SEAS5 hindcasts/forecasts of July 200 hPa U in tropical western Africa. Pearson correlations between model hindcasts/forecasts and observations are listed in each panel, with Spearman rank correlations listed in parentheses.

predictors in combination can provide skillful seasonal hurricane forecast guidance. We linearly regress ACE against the SEAS5 forecasts of the three predictors, with each predictor's weight being calculated directly by the linear regression. Figures 3a–3c display the cross-validated hindcasts for seasonal ACE in March, May, and June, respectively. The model provides skillful forecasts at all lead times, with the predictive capability of the model increasing, especially when using rank correlations, from a March initialization to a June initialization. The three-predictor scheme correlates with ACE at r = 0.60 (r_{rank} = 0.59) in March, r = 0.62 (r_{rank} = 0.65) in May, and r = 0.67 (r_{rank} = 0.71) in June. The model does not have perfect forecast success, however. In 1996, the model significantly underforecast ACE, largely due to a forecast of much cooler July SSTs in the subtropical eastern Atlantic than were observed. In 2004, the model correctly predicted an extremely active hurricane season at the March initialization time, but SEAS5 incorrectly forecast the trade wind predictor to be stronger than observed at the May and June initialization times, leading to a decreasing ACE forecast at those times.

Table 1 examines the correlations between each predictor at the March, May, and June initialization times with ACE as well as the p value for each predictor in the linear regression model at each lead time. Predictors with larger p values are given less weight in the linear regression scheme. For example, the July 10 m U

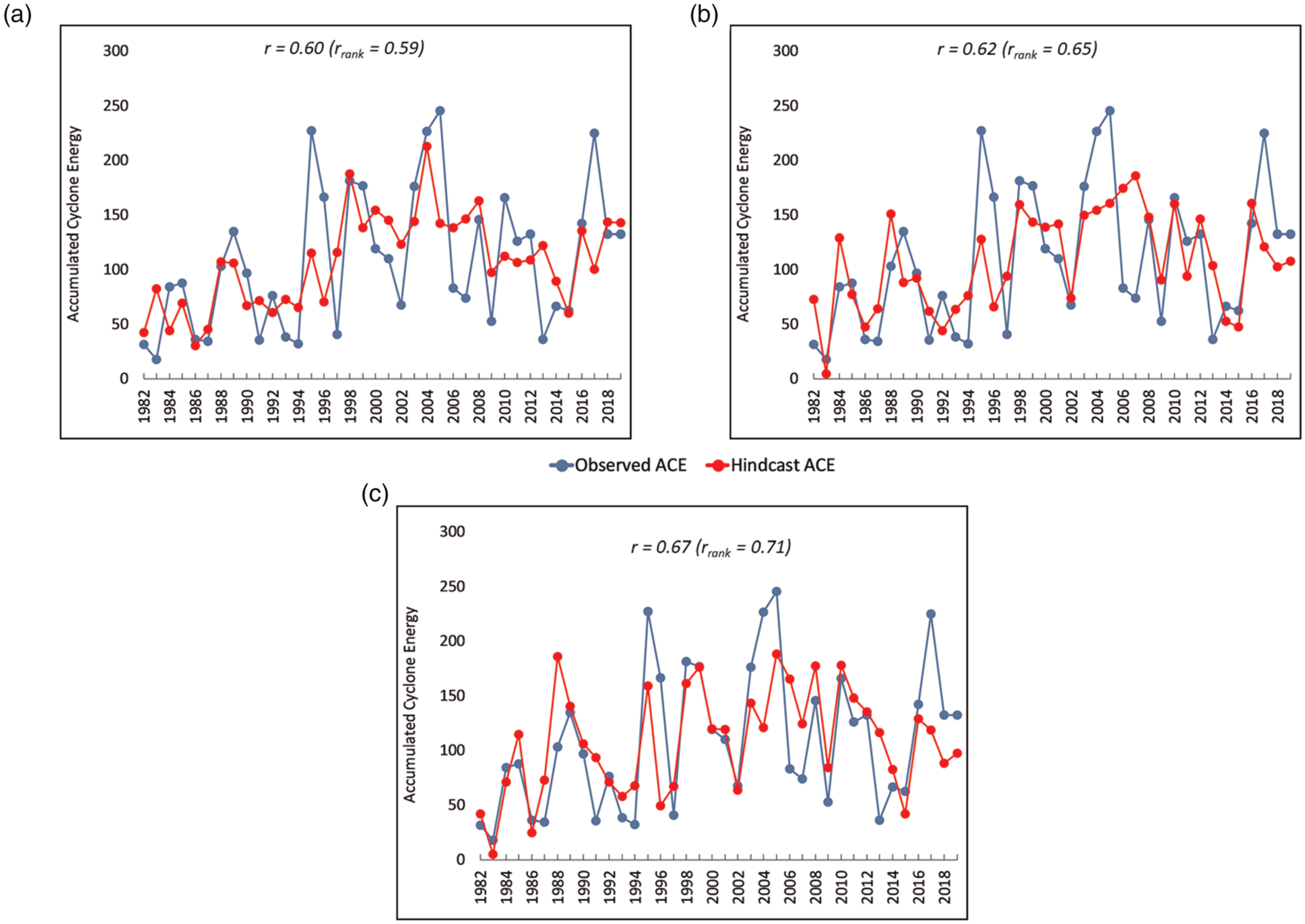

Figure 3. Statistical/dynamical hybrid model hindcasts for seasonal ACE based on March, May, and June initializations. (a) March SEAS5 statistical/dynamical hybrid model hindcasts of seasonal ACE. (b) May SEAS5 statistical/dynamical hybrid model hindcast of seasonal ACE. (c) June SEAS5 statistical/dynamical hybrid model hindcasts of seasonal ACE. Pearson correlations between model hindcasts and observations are listed in each panel, with Spearman rank correlations listed in parentheses.

predictor has a very high p value in the March initialization, and consequently, its predicted value is given very little weight in the statistical/dynamical model at that lead time. By the June initialization, all predictors have p values less than 0.10, indicating that all contribute significantly at the 10% level to the linear regression model.

We now examine the hindcast skill of CSU's seasonal hurricane forecast scheme by using a combination of the currently available statistical model and the statistical/dynamical model. For this analysis, we do a simple arithmetic average of the statistical model and the statistical/dynamical model to arrive at the combined model for the April forecast. For the June and July forecasts, we weigh the statistical model 70% and the statistical/dynamical model 30%, since that is the approximate weight given to these two models if a simple linear regression of the two models was used to forecast ACE. Figures 4a–4c display the cross-validated hindcasts of the combined model for seasonal ACE issued at each lead time, while Figure 4d summarizes the skill of each scheme individually as well as the combined scheme.

The statistical/dynamical model generally shows slightly lower levels of skill than the statistical model at each lead time, with the combination of the statistical and statistical/dynamical models showing improved skill from either model individually for all three outlooks. The largest improvement was noted for the April

Table 1
Pearson Correlation of Individual Predictors With Seasonal ACE at March, May, and June Initialization Times

Predictor	Correlations with ACE			*p*-value in linear regression model		
	March	May	June	March	May	June
July 10 m U	0.39 (0.46)	0.47 (0.58)	0.65 (0.74)	0.95	0.58	0.05
July SST	0.59 (0.61)	0.46 (0.46)	0.55 (0.61)	<0.01	<0.01	<0.01
July 200 hPa U	−0.45 (−0.46)	−0.53 (−0.54)	−0.53 (−0.51)	0.04	<0.01	0.07

Note. Spearman rank correlations are provided in parentheses. Also listed are *p* values for each predictor at each lead time in the linear regression model.

forecast, with the correlation increasing from 0.64 for the statistical model to 0.69 for the combined model using the Pearson correlation coefficient. We note that improvements in skill for individual outlooks are not statistically significant at the 5% level, using Fisher's *r*-to-*z* transformation for the Pearson correlation coefficient (Lee & Preacher, 2013). Nevertheless, the improvements in skill are encouraging and may yield further increases using several ideas that we outline in section 5.

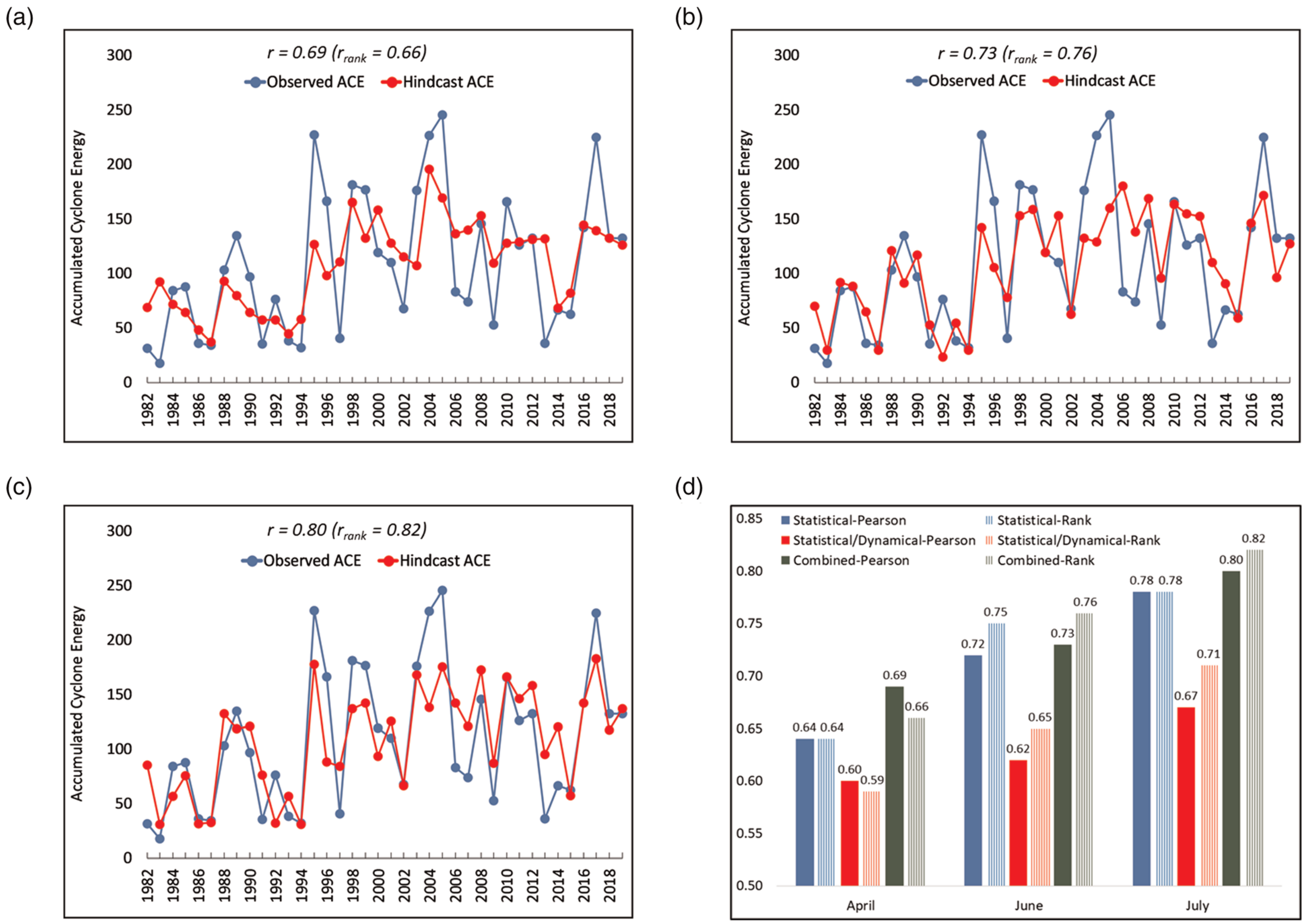

Figure 4. Combined model hindcasts for seasonal ACE based on March, May, and June initializations from 1982–2019 and skill summary of all models. (a) Combined March SEAS5 ACE and early April statistical model ACE hindcasts. (b) Combined May SEAS5 ACE and early June statistical model ACE hindcasts. (c) Combined June SEAS5 ACE and early July statistical model ACE hindcasts. (d) Correlation summary of the statistical model, the statistical/dynamical model, and the combined model for each lead time. Pearson correlations between model hindcasts and observations are displayed with solid bars, while rank correlations between model hindcasts and observations are displayed with bars using vertical hashing.

5. Summary and Future Work

This paper summarizes a first attempt at a statistical-dynamical hybrid model at CSU. The SEAS5 forecast system from ECMWF is able to skillfully forecast the three predictors comprising the early August statistical model by as early as a 1 March initialization date. The three predictors in combination explain ~35% of the variance in ACE with a 1 March initialization, increasing to ~45% of the variance with a 1 June initialization. Improvements in hindcast skill can be achieved by blending the statistical-dynamical model with the currently existing statistical model at all lead times, with the most notable improvement occurring with the early April forecast. In early April, the combined model correlates at 0.69 with ACE, compared with 0.64 for the statistical model. By early July, the combined model explains ~65% of the variance in seasonal ACE.

In the future, CSU will examine the utility of including additional climate models, such as the GloSea5 forecast system (MacLachlan et al., 2015) from the U.K. Met Office to create an ensemble statistical-dynamical hybrid forecast. We will also investigate the use of other regions to improve the skill of the statistical/dynamical hybrid scheme, since the optimum predictor regions in climate models might not be the same as in the observations. In addition to forecasting large-scale fields in July, we will examine if the skill of the statistical/dynamical model can be improved by forecasting large-scale fields during the climatological peak of the Atlantic hurricane season from August–October. Combined with the new statistical models developed by CSU for the 2020 Atlantic hurricane season (e.g., Klotzbach et al., 2020a, 2020b, 2020c, 2020d), these new techniques should help improve the outlooks issued by CSU in the years to come.

Data Availability Statement

The data used in this manuscript are available from the following sources: HURDAT2 (https://www.aoml.noaa.gov/hrd/hurdat/hurdat2.html), ERA5 (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels-monthly-means?tab=form), SEAS5 (https://cds.climate.copernicus.eu/cdsapp#!/dataset/seasonal-monthly-single-levels?tab=form), and NOAA OI SSTv2 (https://psl.noaa.gov/data/gridded/data.noaa.oisst.v2.highres.html).

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