

Multiseason Lead Forecast of the North Atlantic Power Dissipation Index (PDI) and Accumulated Cyclone Energy (ACE)

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ABSTRACT

By considering the intensity, duration, and frequency of tropical cyclones, the power dissipation index (PDI) and accumulated cyclone energy (ACE) are concise metrics routinely used to assess tropical storm activity. This study focuses on the development of a hybrid statistical–dynamical seasonal forecasting system for the North Atlantic Ocean's PDI and ACE over the period 1982–2011. The statistical model uses only tropical Atlantic and tropical mean sea surface temperatures (SSTs) to describe the variability exhibited by the observational record, reflecting the role of both local and nonlocal effects on the genesis and development of tropical cyclones in the North Atlantic basin. SSTs are predicted using a 10-member ensemble of the Geophysical Fluid Dynamics Laboratory Climate Model, version 2.1 (GFDL CM2.1), an experimental dynamical seasonal-to-interannual prediction system. To assess prediction skill, a set of retrospective predictions is initialized for each month from November to April, over the years 1981–2011. The skill assessment indicates that it is possible to make skillful predictions of ACE and PDI starting from November of the previous year: skillful predictions of the seasonally integrated North Atlantic tropical cyclone activity for the coming season could be made even while the current one is still under way. Probabilistic predictions for the 2012 North Atlantic tropical cyclone season are presented.

1. Introduction

The seasonal forecast of North Atlantic Ocean tropical cyclone activity has been the subject of intense scientific investigation (e.g., Jagger and Elsner 2010; Klotzbach 2008) [consult Camargo et al. (2007) for a review]. The capability of performing skillful forecasts has important social and economic impacts, but also represents a way of testing our understanding of the physical processes responsible for the genesis, development, and tracking of these events. Seasonal forecasts for the North Atlantic basin date back almost three decades, starting with the work by Gray (Gray 1984a,b).

Ever since the 1980s, different techniques have been proposed and developed to forecast tropical cyclone activity. Broadly speaking, one can consider two main

approaches to the seasonal forecast of tropical cyclones: one in which dynamical models are used directly to forecast the tropical cyclone activity (e.g., Vitart 2006; Vitart et al. 2007; LaRow et al. 2010; Smith et al. 2010; Zhao et al. 2010; Alessandri et al. 2011; Chen and Lin 2011), and one in which statistical models are developed to connect the future state of North Atlantic tropical cyclone activity to predictors based on the past and present state of climate (e.g., Elsner and Jagger 2006; Klotzbach and Gray 2009; Wang et al. 2009). As an intermediate approach in this broad classification, one can consider hybrid statistical–dynamical models, in which a statistical model, built either on observed relationships (e.g., Kim and Webster 2010) or on the sensitivity of tropical cyclones in high-resolution dynamical model experiments covering a wide range of climate states (e.g., Vecchi et al. 2011; hereafter V11), is applied to the output of dynamical predictions of the future state of climate.

Considerable effort has been placed on the seasonal forecast of the number of tropical cyclones or hurricanes

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(e.g., Vitart 2006; Vitart et al. 2007; Klotzbach and Gray 2009; Wang et al. 2009; Kim and Webster 2010; LaRow et al. 2010; Smith et al. 2010; Zhao et al. 2010; V11; Alessandri et al. 2011; Chen and Lin 2011; Vecchi et al. 2013). In contrast, other tropical cyclone-related quantities, such as the accumulated cyclone energy (ACE; Camargo and Sobel 2005; Bell and Chelliah 2006) and the power dissipation index (PDI; Emanuel 2005, 2007), have received much less attention in the seasonal tropical cyclone prediction literature (e.g., Saunders and Lea 2005; Camargo and Barnston 2009), even though different groups routinely issue ACE forecasts in April and May, such as the Met Office, Colorado State University, Tropical Storm Risk, and the National Oceanic and Atmospheric Administration (NOAA). These quantities present an integrated view of the tropical cyclone season, by convolving storm duration, intensity, and frequency. The difference between the two metrics is that the wind speed is squared when computing ACE and cubed when computing PDI. In this study, we focus on the seasonal forecast of ACE and PDI. The seasonal forecasting system proposed in this study is a statistical-dynamical hybrid system, whose statistical component is based and builds on the recent model by Villarini and Vecchi (2012; henceforth VV12) (see section 2a for an overview of the model).

The effort that has gone into building our understanding of seasonal forecasts of North Atlantic tropical cyclones has led to multiple techniques showing skill beginning from April for the North Atlantic tropical cyclone season peaking in August–October (e.g., Elsner and Jagger 2006; Vitart 2006; Vitart et al. 2007; Wang et al. 2009; LaRow et al. 2010; Zhao et al. 2010; Chen and Lin 2011). However, forecasts at longer leads remain a considerable challenge. For example, the group at Colorado State University led by Klotzbach and Gray issued a note on 7 December 2011 stating: “We are discontinuing our early December quantitative hurricane forecast for the next year and giving a more qualitative discussion of the factors which will determine next year’s Atlantic basin hurricane activity. Our early December Atlantic basin seasonal hurricane forecasts of the last 20 years have not shown real-time forecast skill even though the hindcast studies on which they were based had considerable skill” (<http://hurricane.atmos.colostate.edu/forecasts/2011/dec2011/dec2011.pdf>; last accessed 20 June 2012). This statement seems also to reflect the point of view expressed by the American Meteorological Society (2000), that seasonal tropical cyclone forecasts since the mid-1980s have shown “modest forecast skill” when issued in early June and that “these forecasts have diminishing skill when issued several months before the beginning of the season.”

So, is skillful seasonal forecast of North Atlantic tropical cyclone activity with a 6–9-month lead time not achievable? V11 argued, based on a suite of retrospective forecasts, that it may be possible to make skillful forecasts of North Atlantic hurricane activity from November of the previous year. In this manuscript, we show through a series of retrospective forecasts that it is also possible to perform skillful forecast of North Atlantic PDI and ACE from as early as November of the previous year. Taken together, these results suggest that it would be possible to skillfully forecast the upcoming season even as the current one is coming to an end.

The paper is organized in the following way. In section 2, we describe the data and provide an overview of the statistical framework. Section 3 presents the results of the analyses, and section 4 summarizes the main points of the study and concludes the paper.

2. Data and methodology

a. Statistical model and covariates

In this study, we use the seasonally integrated North Atlantic PDI and ACE values for the period 1949–2011. The time series for these two indexes are computed from the NOAA Atlantic basin hurricane database (HURDAT) (e.g., Jarvinen et al. 1984; MacAdie et al. 2009). The database provides the location (latitude and longitude), minimum pressure, and maximum wind speed of the center of circulation for recorded tropical storms from 1851 to the present. Similar to VV12, we correct the pre-1970 wind speed values according to Landsea (1993), use wind speed values only from tropical and subtropical nondepression (maximum winds $> 17 \text{ m s}^{-1}$) stages of the storms, and focus on the 1949–2011 period to limit the impact of data inhomogeneities.

Let us indicate with Y the seasonally integrated North Atlantic PDI or ACE (PDI is normalized by a factor 10^{11} and ACE by a factor 10^9). Similar to VV12, we can model Y using a gamma distribution

$$f_Y(y | \mu, \sigma) = \frac{1}{(\sigma^2 \mu)^{1/\sigma^2}} \frac{y^{-1+1/\sigma^2} \exp[-y/(\sigma^2 \mu)]}{\Gamma(1/\sigma^2)}, \quad (1)$$

in which the location parameter μ is a linear function of tropical Atlantic (SST_{Atl}) and tropical mean (SST_{Trop}) sea surface temperatures (via a logarithmic link function):

$$\mu = \log(\beta_0 + \beta_{\text{Atl}} SST_{\text{Atl}} + \beta_{\text{Trop}} SST_{\text{Trop}}), \quad (2)$$

and σ is constant. The mean is equal to μ , while the variance is equal to $\mu^2 \sigma^2$.

The selection of these two predictors is supported by physical considerations and results from dynamical

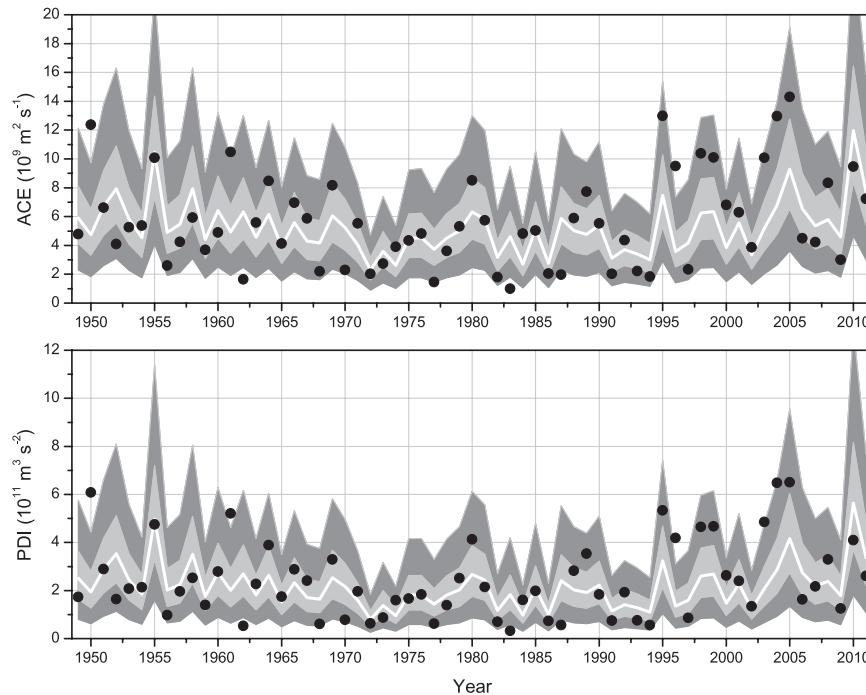


FIG. 1. Results of the statistical modeling of (top) ACE and (bottom) PDI over the period 1949–2011. These results are based on fitting the observational record [corrected according to Landsea (1993); black circles] using a gamma distribution in which the location parameter μ is a linear function of SST_{Atl} and SST_{Trop} (via a logarithmic link function) and constant scale parameter σ . The SST data are based on ERSSTv3b. The white line represents the median (50th percentile); the dark gray area represents the region between the 5th and 95th percentiles, while the light gray area represents the region between the 25th and 75th percentiles.

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numerical and statistical models (e.g., Shen et al. 2000; Sobel et al. 2002; Tang and Neelin 2004; Latif et al. 2007; Vecchi and Soden 2007; Vecchi et al. 2008; Ramsay and Sobel 2011; Villarini et al. 2010, 2011, 2012; V11; VV12). The SST anomalies are computed with respect to the period 1982–2005. The SST_{Atl} anomalies are computed over the tropical cyclone main development region (10° – 25° N and 80° – 20° W), while SST_{Trop} are computed with respect to the tropical belt 30° S– 30° N. We use NOAA's Extended Reconstructed SST dataset, version 3b (ERSSTv3b; Smith et al. 2008), averaged over the period June–November as reference. As shown in Fig. 1 and described in details in VV12, this parsimonious model is able to describe very well the interannual and multidecadal variability exhibited by the observational record.

b. Seasonal forecasts

Similar to V11, we use the forecasts of June–November SST_{Atl} and SST_{Trop} obtained from the NOAA–Geophysical Fluid Dynamics Laboratory (GFDL) experimental seasonal-to-interannual (S–I) prediction system, which is built on the GFDL Climate Model,

version 2.1 (CM2.1; Delworth et al. 2006), and initialized using the coupled ensemble Kalman filter scheme of Zhang et al. (2007). The GFDL CM2.1 forecasts consist of a set of retrospective predictions initialized over the period November 1981–February 2012, each with a 10-member ensemble initialized from the first day of every month with an integration of 12 months.

The model presented in the previous subsection (gamma distribution with μ that is a function of the two predictors and constant σ) provides the structure for our seasonal forecasting system. The seasonal forecasts are obtained computing 10 values of μ from Eq. (2) (one per ensemble member) and then use a Monte Carlo approach to generate the PDI and ACE forecast distributions.

For the retrospective forecasts, the values of the coefficients β_0 , β_{Atl} , and β_{Trop} [Eq. (2)], and σ , however, are not constant over the entire period, but are recomputed from year to year as new information becomes available over the forecast period 1982–2011. For instance, the seasonal forecast for 1982 is based on SST forecasts for 1982 and the model's parameters are estimated using PDI and ACE data as well as ERSSTv3b data from 1949 to 1980. Similarly, the seasonal forecast

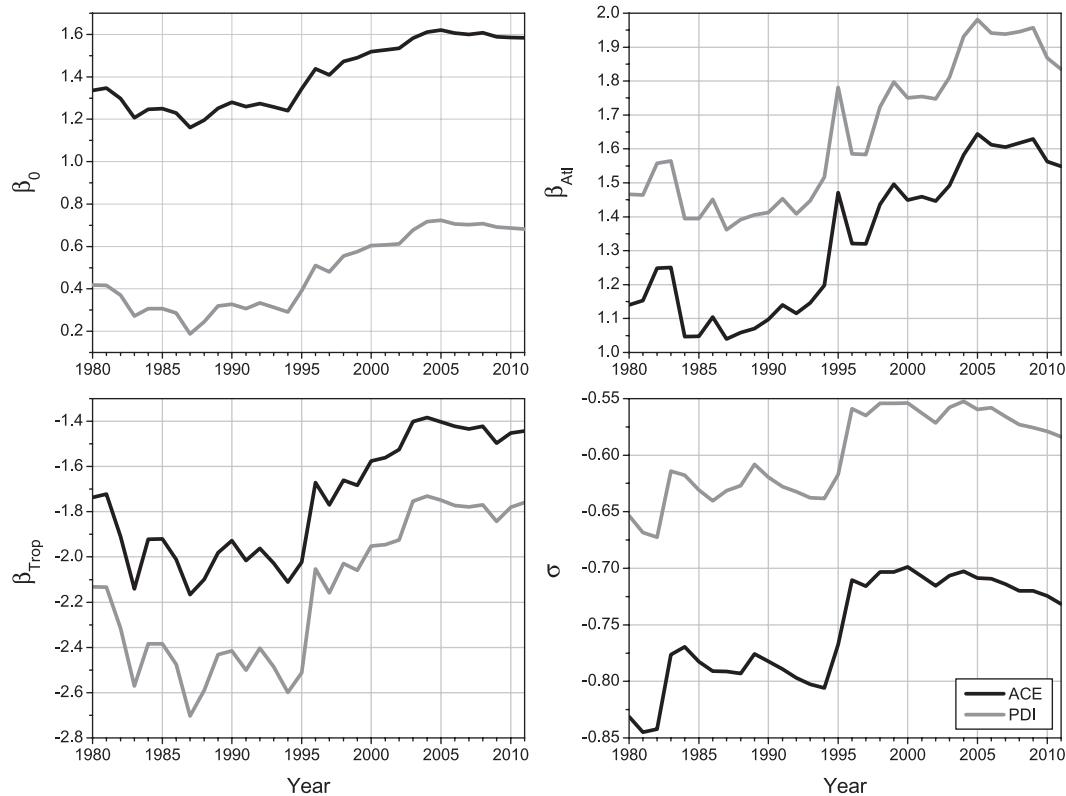


FIG. 2. Time series of the model coefficients for the location parameter μ [Eq. (2)] and scale parameter σ over the period 1980–2011 for ACE (black line) and PDI (gray line).

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for 1983 is based on SST forecasts for 1983 and the model's parameters are estimated using PDI, ACE, and ERSSTv3b from 1949 to 1981. We repeat this for every year from 1982 to 2011. We do not use, for instance, the coefficients estimated including the information for 1981 to forecast the 1982 activity because the final "best track" values (including postseason adjustments) for the 1981 season would not have been available in late 1981 and early 1982. As a sensitivity test, we also perform retrospective forecasts training the statistical model on the entire data record—although this is not a true retrospective forecast, as it requires "future" information (i.e., the full 1949–2011 record was not available until 2012).

Examination of the time series of the model's coefficients highlights some interesting features (Fig. 2). We can clearly see two main regimes, pre-1995 and post-1995, in both PDI and ACE. Around 1995 there is an abrupt shift in the time series of the coefficients, with the differences between the coefficient for SST_{Atl} and SST_{Trop} becoming larger, pointing to a heightened tropical cyclone activity. Not only do we observe an increase in PDI and ACE magnitude as a consequence of the changes in the beta coefficients, but we also have a

similar abrupt change in σ , indicating an increase in variability. The 1995 changepoint is coincident with the abrupt change in tropical cyclone activity (e.g., Elsner et al. 2004; Li and Lund 2012), which was connected to changes in the state of the northern Atlantic Ocean that had wide-ranging impacts (e.g., Knight et al. 2005; Sutton and Hodson 2005; Zhang and Delworth 2006). Predicting these abrupt shifts in the future will be important to improving our seasonal and long-lead forecast of North Atlantic tropical cyclone activity (Smith et al. 2010; Vecchi et al. 2013). It appears that this abrupt shift revealed statistical relationships between SST and PDI/ACE that the shorter record did not. This shift in the character of the statistical model highlights the difficulties inherent in training models on finite datasets: as the record lengthened, the underlying relationships between the predictors and predictand were refined. At the present time, it is unclear what physical mechanisms were behind this abrupt change in the statistical model parameters, but the 1994/95 climate shift in the Atlantic revealed a stronger role for Atlantic SSTs in controlling tropical cyclone activity than one would have inferred from prior data. A question that, unfortunately, we cannot answer at this stage is whether the fit of PDI

and ACE to the SST predictors has converged, or if future shifts in the climate system will result in further refinement of the model.

For the seasonal forecasts initialized in February, March, and April, we consider an additional model configuration. It may be reasonable to expect that by February the best-track PDI and ACE values from the season that has just ended would be available, and one could use these values to compute the most recent set of model coefficients. Therefore, for instance, if one wanted to forecast the PDI and ACE values for 1982, one could use the coefficients estimated using all the information up to 1981, instead of being restricted to the 1949–80 period. We will show that, by adding this additional piece of information, the forecasting PDI and ACE from February, March, and April nominally increases.

The approach we follow is similar to the “retroactive validation” discussed in Mason and Baddour (2007) (see also Villarini and Serinaldi 2012), and differs from the common “calibration-validation approach.” In our case, the forecast method over the validation period is heterogeneous because the statistical model from which these values are obtained is not fitted over a fixed period, but over a changing one. This approach, however, results from using the additional information that becomes available from year to year, and has been already used in other studies and disciplines (e.g., Weron 2006; Villarini and Serinaldi 2012).

We use the median as our best estimate because of its robustness and the skewness in the ACE and PDI distribution, and the forecast accuracy is quantified using four metrics: the Pearson correlation coefficient, the Spearman correlation coefficient, the root-mean-squared error (RMSE), and the mean absolute error (MAE) (e.g., Wilks 2006; Hyndman and Koehler 2006). The first two metrics quantify the degree of agreement between observations and forecasts. The Pearson correlation coefficient quantifies the degree of linear dependence between observations and forecasts. If we indicate the observations with O and the forecasts with F , it is computed as the covariance between O and F normalized by the product of the standard deviation of O and F . The Spearman correlation coefficient can be considered the nonparametric counterpart of the Pearson correlation coefficient and is equivalent to computing the Pearson correlation coefficient on the ranked observations and forecasts. Therefore, the Spearman correlation coefficient is less sensitive to outliers and quantifies the degree of monotonic dependence between O and F . The use of MAE and RMSE aims at quantifying the discrepancies between observations and forecasts, with the latter penalizing more the large discrepancies (e.g., Hyndman and Koehler 2006).

Evaluation of the probabilistic forecast is based on the method presented in Laio and Tamea (2007) for the verification of probabilistic forecasts for continuous predictands. Given an observed value x_i , we can compute the probability $z_i = P_i(x_i)$, with the distribution of z_i that follows a standard uniform distribution and the z_i that should be independent for a correct probabilistic forecast. We examine the validity of the independence assumption by computing the autocorrelation functions and testing whether autocorrelation values are statistically different from 0. We assess the goodness-of-fit of the standard uniform distribution using probability plots, in which we plot z_i against their empirical cumulative distribution function R_i/n , where R_i is the rank of the i th observation and n is the sample size. If the data are approximately uniform, the points $(z_i, R_i/n)$ are located along the $x = y$ line. Because of sampling uncertainties from the limited sample size, we also include the Kolmogorov 5% significance bands. These graphical results also provide information about possible reasons for the deviation from uniformity, in case the uniformity test is not passed. Consult Laio and Tamea (2007) for more details.

3. Results

We use the parsimonious statistical model discussed in the previous section to perform a retrospective forecast for every year from 1982 to 2011. Figures 3 and 4 show the results for ACE and PDI for different initialization months (description of the retrospective forecast skill for the two SST predictors is presented in V11). The models we have developed are able to describe the interannual variability exhibited by the data as early as November, indicating that it is possible to make skillful forecasts of North Atlantic PDI and ACE as early as November of the previous year. The November forecast (7-month lead time for a tropical cyclone season starting in July) is able to capture the observed alternation of quieter and more active periods. As the lead time decreases, the median tends to follow more closely the observations, and the forecast distribution tends to better describe the data. The agreement between median forecasts and observations tends to increase going from November to January and February, likely because of an improvement in the SST forecast (V11). On the other hand, the March and April forecasts tend to be worse than the previous ones, with decreased interannual variability and a poorer agreement between median forecast and observations. These statements are valid for both ACE and PDI forecasts. This worsening in the seasonal forecast performance when initialized in March and

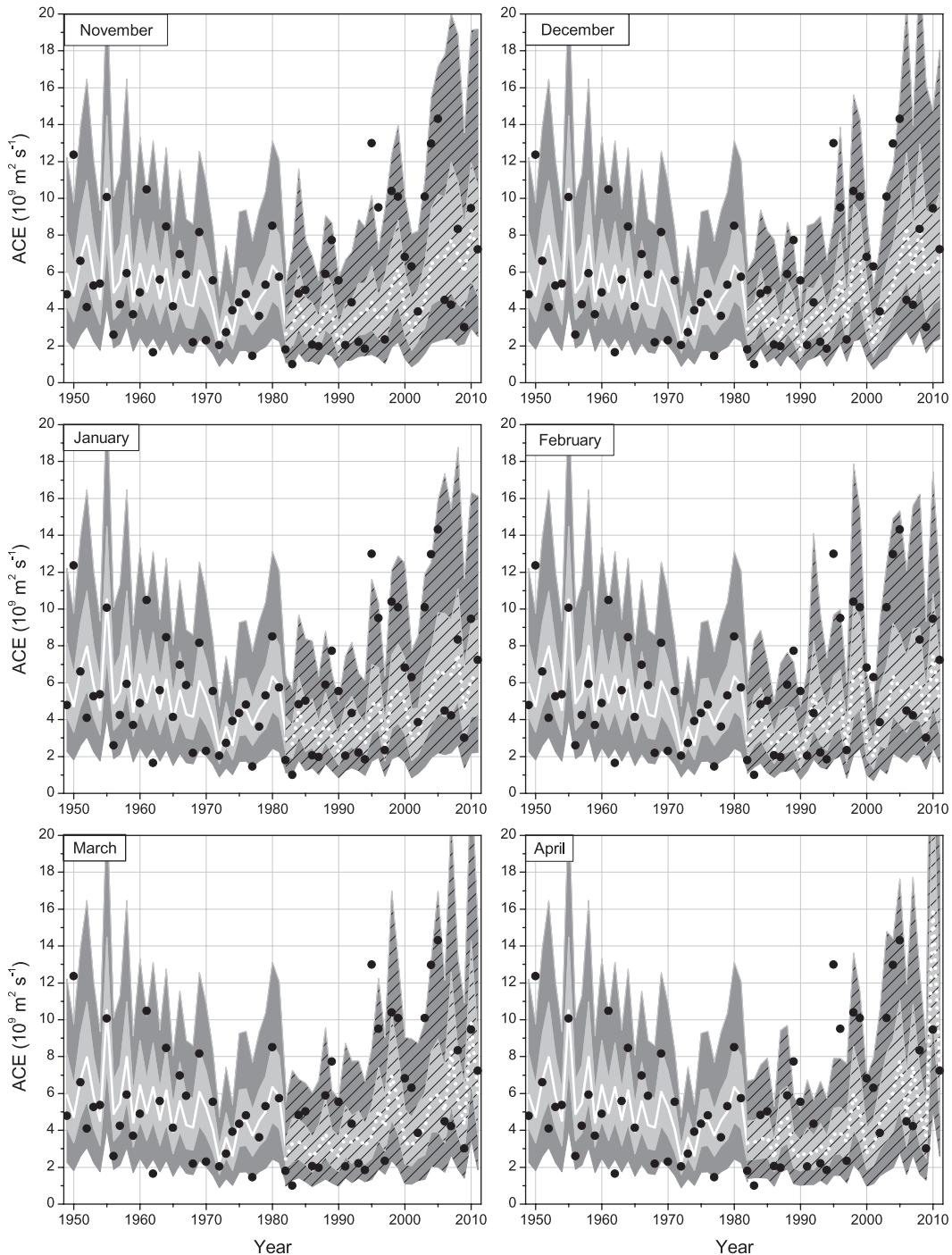


FIG. 3. Seasonal forecast of ACE initialized from November (of the year prior to the one to forecast) to April (same year as the one to forecast). The black circles represent the observations. The white line represents the median (50th percentile); the dark gray area represents the region between the 5th and 95th percentiles, while the light gray area represents the region between the 25th and 75th percentiles. The hatched regions represent the forecast period.

April was also noted for hurricane frequency in V11. They found that the correlation between observation and forecast of tropical Atlantic SST using GFDL CM2.1 peaked in January and progressively decreased

in February, March, and April. The correlation between observed and forecast tropical mean SST exhibited a similar pattern, with the worst agreement in the April forecasts.

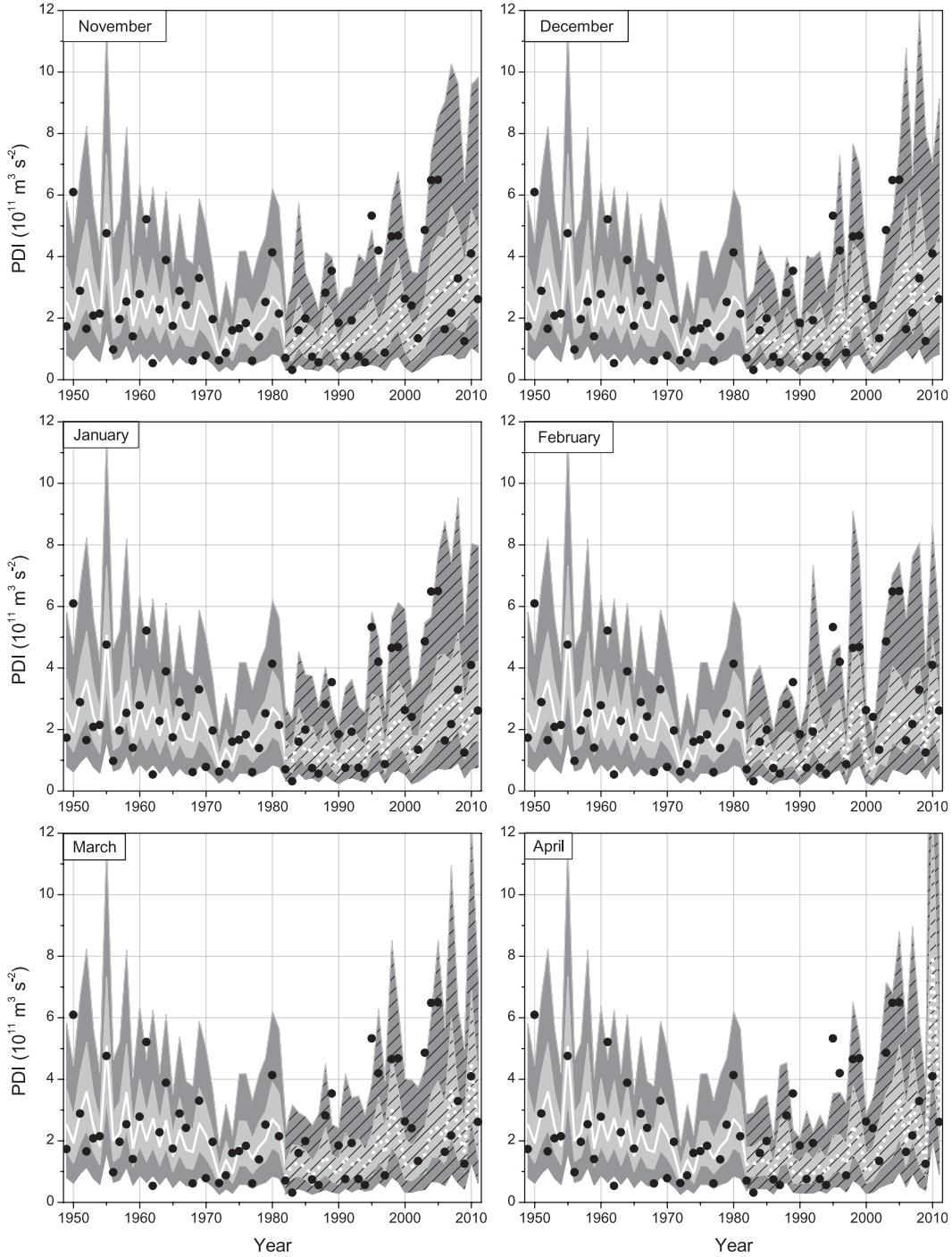


FIG. 4. As in Fig. 3, but for the PDI.

Figure 5 summarizes the results regarding the accuracy of the seasonal forecast of ACE (left panels) and PDI (right panels) using the four metrics described in the previous section. Consistent with the visual assessment of Figs. 3 and 4, we observe an increase in performance from November to January and February, and

then a worsening in March and April. The MAE for ACE decreases from 2.8×10^9 to $2.7 \times 10^9 \text{ m}^2 \text{ s}^{-1}$ to increase again to about $3.0 \times 10^9 \text{ m}^2 \text{ s}^{-1}$ in April. The MAE for PDI shows a similar pattern, with values of about $1.3 \times 10^{11} \text{ m}^3 \text{ s}^{-2}$ in November and December, decreasing to about $1.23 \times 10^{11} \text{ m}^3 \text{ s}^{-2}$ in January and February, and

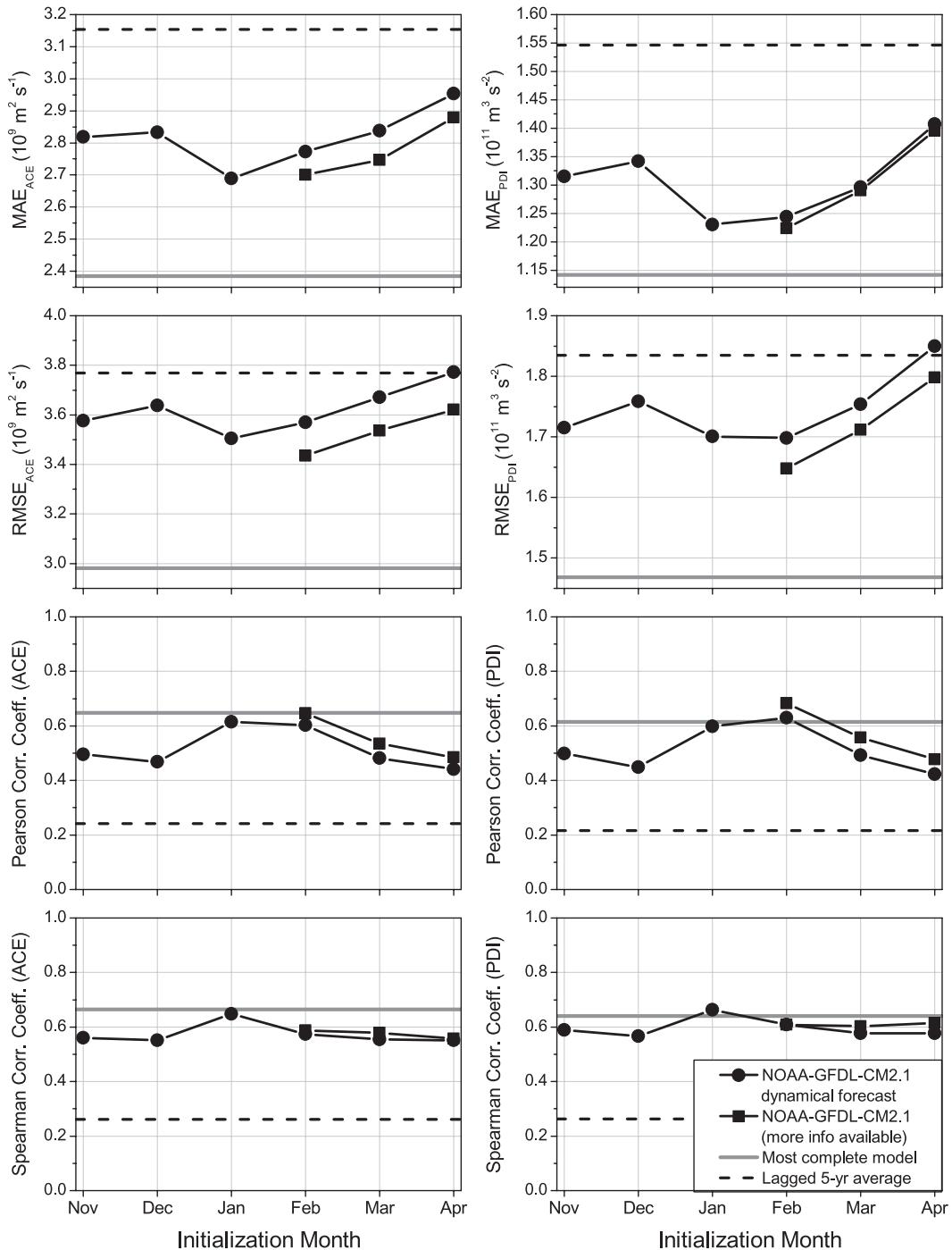


FIG. 5. Summary of the accuracy of the seasonal forecast of (left) ACE and (right) PDI for different initialization months. The metrics used are MAE, RMSE, and the Pearson and Spearman correlation coefficients. The gray horizontal line (most complete model) represents the results obtained by using the median from Fig. 1 as reference value. The black lines with black circles represent the results using the medians from Figs. 3 and 4. The black lines with black squares represent the results for the model configuration using the coefficients of the statistical model estimated using all the information available for that year, and the SST forecast for the upcoming year. The lagged 5-yr average (dashed black line) is used as measure of “null skill” as recommended in World Meteorological Organization (2008).

increasing again reaching $1.4 \times 10^{11} \text{ m}^3 \text{ s}^{-2}$ in April. The RMSE values are larger than the corresponding MAE values because of the increased influence of discrepancies at the extremes, and the skewed distribution of ACE and PDI. Both measures of error are smaller than the observed standard deviations of $3.8 \times 10^9 \text{ m}^2 \text{ s}^{-1}$ and $1.8 \times 10^{11} \text{ m}^3 \text{ s}^{-2}$ for ACE and PDI, respectively.

The results obtained by using the correlation coefficients indicate that this experimental seasonal forecasting system was able to reproduce well the observational record. The Pearson correlation coefficient is about 0.5 for forecasts initialized in November and December, peaking at 0.6 in January and February, and decreases down to 0.5 in March and April. The results are similar for both PDI and ACE. The results obtained by using the Spearman correlation coefficient are less dependent on the initialization month. The values for ACE are on the order of 0.55, with the exception of the January forecast, which peaks at about 0.65. The results for PDI are slightly larger, with values on the order of 0.58 for all the initialization months, except for January, in which the correlation coefficient peaks at 0.66. The slight differences between Pearson and Spearman correlation coefficients can be because of the fact that the latter works on ranks rather than on the numerical values of the forecasts and observations. As shown in Fig. 5, the accuracy of these forecasts represent an improvement over the lagged 5-yr ACE and PDI averages, which are used as measure of “null skill” as recommended in World Meteorological Organization (2008).

We evaluate the probabilistic forecasts using the approach described in Laio and Tamea (2007). The z_i do not exhibit statistically significant autocorrelation based on the autocorrelation functions for any forecast months. We examine the goodness-of-fit of the standard uniform distribution using probability plots (Fig. 6). The points are generally within the 5% confidence intervals pointing to a correct probabilistic forecast, with a slight tendency toward underprediction, with points lying below the $x = y$ line.

As mentioned before, we have also examined the improvement in the forecasts initialized in February to April associated with the use of the most recent PDI, ACE, and SST values. Overall, the February forecasts are now more accurate than the January ones, exhibiting the smallest MAE and RMSE values and the largest Pearson correlation coefficients (the largest Spearman correlation coefficients are still in January). The use of this additional information results in an overall improvement in the March and April forecasts as well.

We have also used the seasonal forecasting system presented in this study to make forecasts for the

upcoming 2012 tropical cyclone season (Fig. 7, Table 1). Neither the November nor December 2011 forecasts suggested that the 2012 season will be particularly active. According to the ACE forecast, there is an 11.4% probability of having a season exceeding the 1980–2010 mean based on the November forecast, and a slightly larger probability according to the December forecast (17.7%). The results for PDI are similar, with a probability of 10.3% (16.2%) of having a season more active than the 1980–2010 mean based on the November (December) forecasts. On the other hand, based on the forecasts initialized in January and February, the 2012 season is forecast to be about as active as the 1980–2010 mean. The probability of having a season more active than the mean 1995–2010 period is smaller than for the 1980–2010 period, but still increasingly larger going from the November to the February forecasts (Table 1). The increase in forecast activity with reduced lead time is because of the forecast of SST, with a larger forecast warming of the Atlantic Ocean relative to the rest of the tropics. Based on the results in Fig. 5, the retrospective 1982–2011 January and February forecasts were generally more accurate than the November–December ones—but the differences are not statistically significant. It will be interesting to check at the end of the 2012 season how well this forecast system performed.

4. Conclusions

In this study, we have proposed and developed a hybrid statistical–dynamical forecasting system of North Atlantic tropical cyclone activity, targeting the seasonally integrated PDI and ACE values. Predictions of these two indices complement forecasts of the number of storms by also providing information on intensity and duration. Our system builds on VV12 and describes the PDI and ACE time series with a gamma distribution, in which the logarithm of the location parameter depends linearly on tropical Atlantic and tropical mean SSTs, while the scale parameter is constant. We use the GFDL CM2.1 experimental seasonal-to-interannual forecast system (Delworth et al. 2006; Zhang et al. 2007; V11) to obtain the input predictors as early as November of the year prior to the season we want to forecast. We used four different metrics (RMSE, MAE, and the Pearson and Spearman correlation coefficients) to assess the forecast accuracy, and used the approach described in Laio and Tamea (2007) to evaluate the probabilistic forecasts.

By performing retroactive validation (Mason and Baddour 2007), we showed that it is possible to make skillful forecasts of PDI and ACE starting from November of the previous year. This means that there is

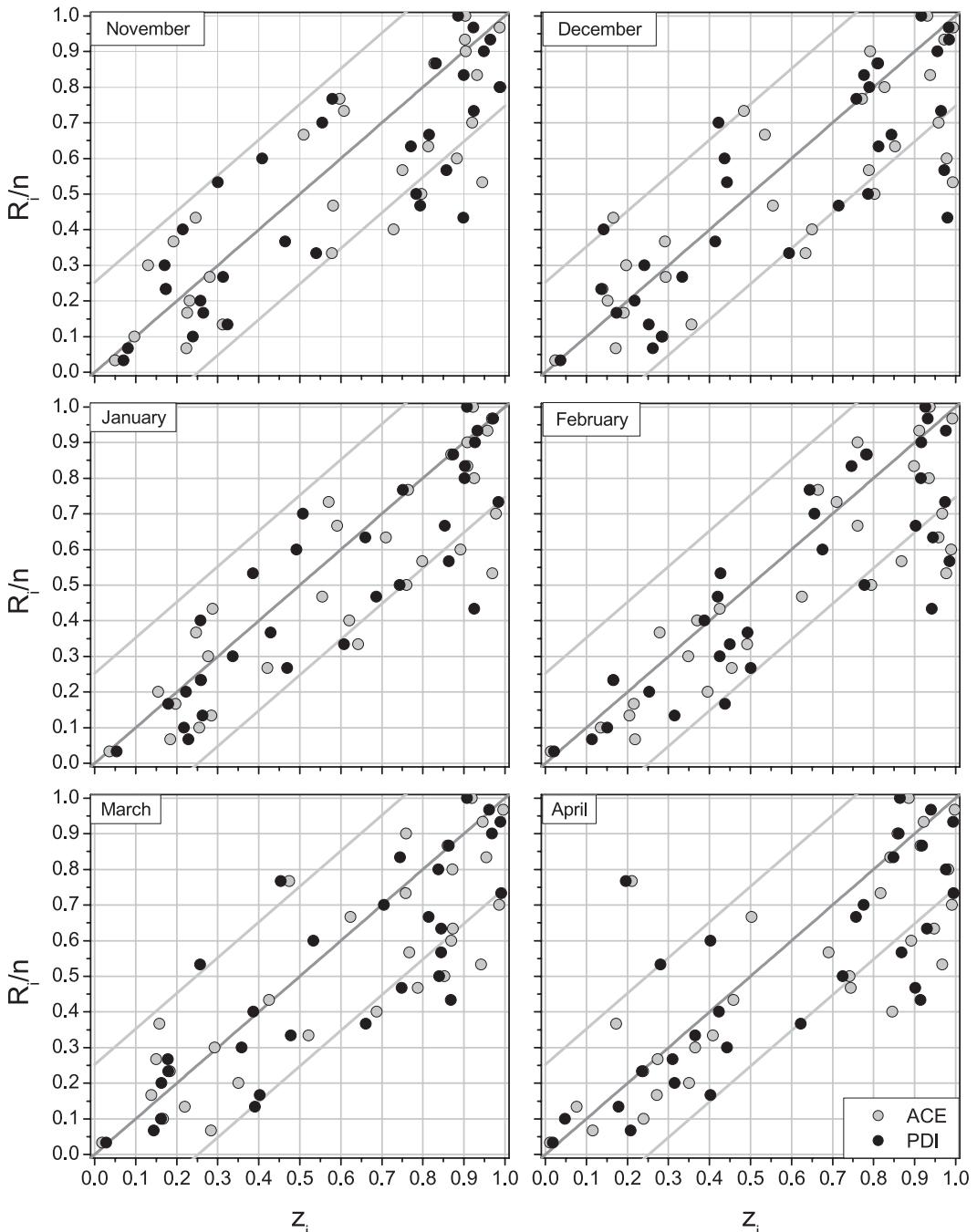


FIG. 6. Probability plot representation of the probabilistic forecast of ACE (gray circles) and PDI (black circles). The light gray solid lines represent the Kolmogorov 5% significance bands.

potential for skillful forecasts of the seasonally integrated North Atlantic tropical cyclone activity for the coming season while the current one is still under way. Moreover, it may be possible to use this forecasting system for the forecast of Arctic sea ice, building on the recent link found between PDI and sea ice cover in the Arctic (Scoccimarro et al. 2012).

Using this system, we have provided ACE and PDI forecasts for the 2012 season. Based on our results, the 2012 tropical cyclone season is not forecast to be particularly active, even though the January and February 2012 forecasts indicate that it will be less inactive than what the November and December 2011 forecasts suggested.

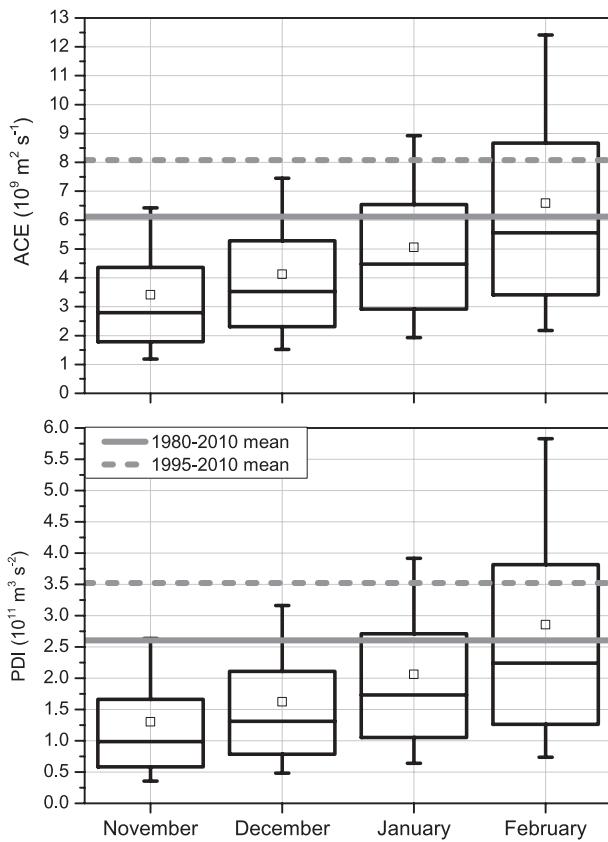


FIG. 7. Seasonal forecast of (top) ACE and (bottom) PDI initialized in November and December 2011, and January and February 2012. The limits of the boxes represent the 25th and 75th percentiles, while the whiskers represent the 10th and 90th percentiles. The line and the square within the box represent the median and mean values, respectively. The ACE and PDI values averaged over the periods 1980–2010 (solid gray line) and 1995–2010 (dashed gray line) are included as reference.

There are several different possible venues to improve upon this system. In this study, we focused on the SST forecasts from the GFDL CM2.1. In the future, however, it would be possible to include SST forecasts from research centers around the world that already routinely perform SST forecasts. Based on the results of V11, it is likely that a multimodel ensemble approach would lead to an increase in the long-lead skill. Another venue for future research is the application of this statistical model to decadal projections of North Atlantic tropical cyclone activity. Smith et al. (2010) and Vecchi et al. (2013) showed that there is potential skill in multiyear predictions of tropical cyclone frequency. Experiments are under way to assess the feasibility of multiyear-to-decadal forecasts of PDI and ACE using the GFDL CM2.1 experimental decadal forecast system (A. Rosati et al. 2012, unpublished manuscript; Yang et al. 2013; Vecchi et al. 2013) and the suite of phase 5 of the Coupled

TABLE 1. Summary of the probabilities of having a 2012 season more active than the 1980–2010 and 1995–2010 means for PDI and ACE and different initialization months.

	Nov	Dec	Jan	Feb
Probability of 2012 season more active than 1980–2010 mean (ACE)	11.4%	17.7%	29.1%	44.3%
Probability of 2012 season more active than 1995–2010 mean (ACE)	4.9%	7.8%	14.0%	28.7%
Probability of 2012 season more active than 1980–2010 mean (PDI)	10.3%	16.2%	27.0%	42.3%
Probability of 2012 season more active than 1995–2010 mean (PDI)	4.7%	7.4%	13.5%	28.4%

Model Intercomparison Project (CMIP5) initialized decadal forecast experiments (Taylor et al. 2012). The results of this study together with those in Smith et al. (2010) and Vecchi et al. (2013) indicate that there is hope in achieving skillful multiyear predictions of ACE and PDI by considering both radiatively forced and internal components of multiyear tropical cyclone activity changes.

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