A Prediction Model for Atlantic Named Storm Frequency Using a Year-by-Year Increment Approach

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ABSTRACT

This paper presents a year-by-year incremental approach to forecasting the Atlantic named storm frequency (ATSF) for the hurricane season (1 June–30 November). The year-by-year increase or decrease in the ATSF is first forecasted to yield a net ATSF prediction. Six key predictors for the year-by-year increment in the number of Atlantic named tropical storms have been identified that are available before 1 May. The forecast model for the year-by-year increment of the ATSF is first established using a multilinear regression method based on data taken from the years 1965–99, and the forecast model of the ATSF is then derived. The prediction model for the ATSF shows good prediction skill. Compared to the climatological average mean absolute error (MAE) of 4.1, the percentage improvement in the MAE is 29% for the hindcast period of 2004–09 and 46% for the cross-validation test from 1985 to 2009 (26 yr). This work demonstrates that the year-by-year incremental approach has the potential to improve the operational forecasting skill for the ATSF.

1. Introduction

This paper presents a year-by-year incremental approach to forecasting Atlantic named storm frequency. Fan et al. (2008) applied it in the seasonal forecast of Yangtze River valley summer rainfall. They defined the difference in any variable between the current year and the previous year as DY, and predicted the DY of the Yangtze River valley summer rainfall instead of the summer rainfall directly. The model showed a high level of accuracy in hindcasting the Yangtze River valley summer rainfall during the period of 1997–2006, with an average relative root-mean-square error of 18%. The year-by-year incremental approach was subsequently applied successfully to the seasonal forecast of northern China summer rainfall (Fan et al. 2009) and northeastern China temperature (Fan 2009a).

So far, the interannual variability of typhoon activity and its seasonal forecast have been studied by a number of groups (Briegel and Frank 1997; Camargo and Sobel 2005; Chan et al. 1998; Ding 1983; Lander 1994; Wang and Chan 2002; Wang et al. 2007; Wang and Fan 2007; Fan 2009c; Lang and Wang 2008; Zhou et al. 2008a,b). Fan and Wang (2009) also extended the approach to forecasting typhoon frequency and discussed the advantages of the approach. They also used the approach in real-time forecasting for the number of landfalling tropical cyclones over China from 2008 to 2009; the absolute errors were zero and one, respectively. Fan et al. (2008) proposed that the rationale for the year-by-year incremental approach may arise from the existence of tropospheric biennial oscillation (TBO) in the Asian monsoon and monsoon rainfall, suggesting that a variable in the year-by-year increment may capture more TBO features and provide more prediction skill than a variable in the original form can.

Nicholls (1992) proposed a difference method for forecasting Australian seasonal tropical cyclone activity and defined the differences in the number of typhoons as the change in typhoon numbers from the last season to the current season. Nicholls also calculated the differences from the September to November Southern Oscillation Index (SOI). The difference in the number of typhoons was predicted on the basis of the differences in September–November SOI. The results show that the difference method provides more hindcast skill in terms of the typhoon numbers during the period 1980–1991 than predicting seasonal typhoon numbers directly from the observed SOI can provide. Nicholls (1992) also pointed out that the use of...
differences in this way may provide a means for avoiding the deterioration of seasonal climate forecast systems in a changing climate or in other circumstances that might lead to nonstationarity in predictive relationships.

Predictions for Atlantic hurricane activity and intensity have been made in several prior studies (Blake and Gray 2004; Elsner and Schmertmann 1993; Gray 1984a,b; Gray et al. 1992; Gray et al. 1993; Gray et al. 1994; Klotzbach and Gray 2004; Klotzbach 2007; Knaff 1997, 1998; Zhang and Kieu 2005). Gray (1984b) developed the first prediction model for annual Atlantic hurricane activity based on three predictors during 1950–82 (33 yr), including the phase of stratospheric quasi-biennial oscillation (QBO), the occurrence and strength of El Niño, and the mean April–May SLP anomalies over the Caribbean Basin. The in-sample hindcast skill (over the 33-yr period), as measured by the correlation coefficient for the number of all storms (hurricanes and tropical storms), was 0.82, which is an explanation of 67% of the interyear variance. Subsequently, Klotzbach and Gray (2009) examined the significant skill of their seasonal hurricane forecasts in early June and early August over the past 25 yr (1984–2008) and further showed the verification of real-time hurricane forecasts for 2004–09 (Klotzbach and Gray 2010).

In this paper, we will aim to apply the year-by-year incremental approach to forecasting Atlantic named tropical cyclones to examine the approach’s prediction capability.

2. Method and dataset

We take the following steps. 1) The DY denotes the difference between the current year and the preceding year in any variable, and the ATSF corresponds to the number of Atlantic named storms (tropical storms and hurricanes) per year. The 1 June–30 November period refers to the hurricane season. For example, the DY of the ATSF in 1998 represents the difference in the ATSF between 1998 and 1997. 2) We analyze the DY of the atmospheric circulation variability that is associated with the DY of the ATSF to identify predictors. 3) We establish a statistical forecast model to predict the DY of the ATSF; the ATSF is derived as the sum of the DY of the ATSF and the previous ATSF. 4) We also validate the statistical model. The essential criteria for defining a tropical named storm include the maximum wind speed exceeding 34 kt. The dataset of the number of Atlantic named storms is obtained from the National Hurricane Center. The National Centers for Environmental Prediction and the National Center for Atmospheric Research’s monthly atmospheric reanalysis, with a resolution of $2.5^\circ \times 2.5^\circ$, is used for the atmosphere circulation analyses (Kistler et al. 2001). The time span of the dataset is 45 yr, covering 1965–2009. The forecast model is established using a multilinear regression method based on data taken from 1965 to 1999 (35 yr). Using the forecast model, we made a hindcast of the ATSF for the period 2000–09 (10 yr).

In the cross-validation section, not only is the forecast year removed but all of the future years should also be removed. In that way, we can have many years of real forecasting. For example, the 1965–83 dataset should be used to forecast 1984, the 1965–85 dataset should be used to forecast 1986, the 1965–86 dataset should be used to forecast 1987, and so on. The cross-validation test is performed to validate the prediction skill of the prediction model for the period of 1984–2009 (26 yr) to compare with the work of Klotzbach and Gray (2009).

To illustrate the prediction skill of the year-by-year incremental approach further, we compare the prediction model using the year-by-year incremental approach (M-DY) with the nondifferenced model (M-P) using the Poisson regression method and the nondifferenced model (M-Y) using the multilinear regression method.

3. The predictors

TBO is one of the significant features of the ATSF during the period 1965–2009 using the wavelet analysis, with the standard deviation of the DY for the ATSF being much larger (5.6) than that of the ATSF itself (4.2), with an average ATSF of 11. The predicted value is therefore selected as the DY of the ATSF, as it captures the TBO features of the ATSF. Gray (1984a) indicated that Atlantic hurricane frequency and stratospheric QBO are hypothesized to be associated with the trade-wind nature of Atlantic cyclone formation; since the publication of that report, he has no longer used QBO in seasonal forecasting.

DelSole and Shukla (2009) pointed out that a prediction model has a large amount of artificial skill due to predictor screening. In choosing the predictors of the DY of the ATSF, two factors should be considered. First, the predictors chosen must be available and easily accessible no later than 1 May to make the forecast 1 month ahead. Second, the predictors should have a physical link with the DY of the ATSF. Therefore, we identify several predictors based on an analysis of the DY of the circulation associated with the DY of the ATSF.

a. The predictors from the previous year

The two predictors that we use are the area-average DY of 200-hPa air temperature over Eurasia ($30^\circ–45^\circ$N, $60^\circ–105^\circ$E) ($X_1$) and over the Atlantic ($30^\circ–40^\circ$N, $45^\circ–15^\circ$W) ($X_2$) in November of the previous year (see Fig. 1a). When the air temperature anomalies are low over Eurasia and high over the Atlantic at upper levels, the DY of the ATSF is increased. At the same time, the negative DY of
the North Atlantic Oscillation (NAO) is remarkable at sea level pressure (SLP; see Fig. 1b). The NAO is well known for its coherent north-to-south seesaw pattern at sea level pressure between Iceland and the Azores. When pressures are low over Iceland (Icelandic low), they tend to be high over the Azores (Azores high) and vice versa. The intensity of the NAO determines the position and orientation of the midlatitude jet stream through variations in the horizontal pressure (geopotential height) gradients. Klotzbach and Gray (2004) took the November 500-hPa geopotential height in the far North Atlantic as a predictor for Atlantic hurricane forecasts. They found that positive values of this November index are correlated with reduced tropospheric vertical wind shear in the following August–October time period to enhance TC development. Elsner and Kocher (2000) revealed a statistical link between global tropical cyclone activity and the NAO. They speculated that the physical mechanism defining this linkage is due to global atmosphere–ocean circulations. Blake and Gray (2004) took the area-average June 200-hPa zonal wind over the far northern region of Greenland (80°–85°N, 45°W–10°E) as a predictor of August Atlantic hurricane activity. They pointed out that when the June 200-hPa zonal wind in this area is anomalously strong from the west, the August Atlantic hurricane rate is enhanced. Blake and Gray (2004) suggested that this connection may reflect midlatitude blocking conditions near Greenland and the negative phase of the NAO. Actually, variations in North Atlantic sea level pressure respond to changes in surface temperature patterns and are physically linked to changes in sea ice formation over the Arctic Ocean, which is related to

Fig. 1. Correlation coefficients between (a) the DY of the ATSF and the DY of the 200-hPa temperature in November of the previous year and (b) SLP. The shaded areas indicate significance at the 95% level estimated by a local Student’s t test.
the North Atlantic component of the global thermohaline circulation (Elsner and Kocher 2000).

b. Predictors from the current year

Another five predictors from the current year have been used in this prediction model. In February, when the DY of air temperature at upper levels (low level) is high (low) over the Antarctic area, the DY of ATSF is increased. A predictor of $$X_3$$ is defined as the area-average DY of 200-hPa air temperature in the region south of 60°S, which is related to the Antarctic Oscillation (AAO) in February and the AAO in the Western Hemisphere in the August–October (ASO) time period (see Fig. 2).

The AAO is known to be a major mode of atmospheric variability in the Southern Hemisphere (Gong and Wang 1999; Thompson and Wallace 2000). Previous studies have linked the AAO with tropical or even extratropical Northern Hemisphere climate variability (Thompson and Lorenz 2004; Fan and Wang 2004; Wang and Fan 2005; Sun et al. 2009; Li 2009). The results suggest that the positive phase of the AAO corresponds to fewer days of dust weather events and less summer rainfall over northern China through the atmospheric meridional teleconnection (Fan and Wang 2004; Wang and Fan 2005). Wang and Fan (2007) documented the relationship between the AAO and typhoon frequency over the western North Pacific. Subsequently, Fan (2009b) considered the zonal asymmetry of the AAO proposed by Fan (2007) and revealed a positive correlation between the AAO in the Western Hemisphere and Atlantic hurricane frequency during JJASO. The meridional teleconnection pattern in the Atlantic sector between the polar region and the tropical Atlantic is responsible for the AAO in the Western Hemisphere and the Atlantic hurricane frequency. Through the meridional teleconnection pattern, the tropical Atlantic exhibits anomalous easterly winds in the higher troposphere as well as anomalous westerly winds in the lower troposphere, which is favorable for the reduction of the vertical shear of the zonal wind in the tropical Atlantic. It is found that $$X_3$$ positively correlates with the phase of the AAO in the Western Hemisphere and a negative SLP in the tropical Atlantic in the ASO, which are favorable for increased ATSF (see Fig. 2).

In March, the central Atlantic DY of SLP (averaged over the region 20°–30°N, 30°–15°W) is used as a predictor. It is known that the prehurricane season low sea level pressure in the Atlantic correlates well with increased Atlantic tropical cyclone activity (Brennan 1935; Ray 1935; Knaff 1997, 1998). Dunn (1940) pointed out that when the Azores high shifts northward, the Bermuda high weakens and hurricane frequency increases over much of the tropical Atlantic, including the Caribbean. An anomalous low pressure area indicates a weak midtropospheric subsidence and less drying of the midatmosphere. Low pressure in the Atlantic Ocean is also associated with reduced trade winds, which is linked to warmer SSTs persisting
from February to June–October (JJASO), partly due to decreased evaporation and upwelling (see Fig. 3).

In April, two predictors are selected from the northwest and North Pacific, respectively. One is the April 200-hPa geopotential height over the northwest Pacific (10°–20°N, 150°–165°E), and the other is the April 200-hPa zonal wind over the North Pacific (45°–65°N, 160°–120°W). The increased 200-hPa geopotential height over the northwest Pacific and the decreased 200-hPa zonal wind over the North Pacific tend to promote increased ATSF. Figure 4 shows that two predictors are associated with the intensity of the subtropical high over the northwest Pacific and the North Pacific Oscillation (NPO). Blake and Gray (2004) noted that an enhanced June subtropical high over the northwest Pacific and a low SLP anomaly over the Bering Sea region tend to increase in the number of August Atlantic hurricanes. It is well known that the NPO is a major mode in the interannual atmospheric variability in the North Pacific, indicating the seesaw pattern of sea level pressure variability between high and low latitudes in the Pacific (Rogers 1981). Wang et al. (2007) found that the July–September NPO is positively correlated with the annual number of typhoons occurring in the western North Pacific and negatively correlated with the annual number of the Atlantic hurricanes for the period 1949–98; here, NPO is defined as the normalized SLP difference between points P1 (65°N, 170°E) and P2 (25°N, 165°E) in the North Pacific, where positive NPO represents a weakened Aleutian low and a weakened northwest Pacific subtropical high, and vice versa. They suggested that a positive phase of NPO is concurrent with an increase in the magnitude of the vertical wind shear between 150 and 850 hPa in the tropical Atlantic, as well as decreased magnitude in the vertical wind shear in the major typhoon genesis region of the western North Pacific. Thus, it is favorable to a decrease in the number of Atlantic tropical cyclones and an increase in the western North Pacific, and vice versa. The large-scale pattern of the NPO–MWS correlation coefficient (where MWS is magnitude of the wind shear) is shown as well-organized teleconnection patterns. One is from the North Pacific to the western North Pacific, and the other is from the North Pacific to the tropical Atlantic, along with alternative positive and negative values. It is suggested that the magnitudes of the vertical zonal wind...

![Diagram](image-url)  
**Fig. 4.** Correlation coefficients between the DY of SLP in April and (a) $X_5$ and (b) $X_6$. The shaded areas indicate significance at the 95% level estimated by a local Student’s $t$ test.
shears in the western North Pacific and the tropical Atlantic are linked with the NPO through these two teleconnection patterns. The NPO-related SST pattern also shows a positive (negative) correlation in the tropical Pacific (Atlantic). Subsequently, several predictors related to the NPO have been included in the seasonal forecasts of typhoon frequency over the western North Pacific (Fan 2007; Fan and Wang 2009).

c. Summary of predictors

Six predictors are identified. Among them, $X_1$ is the area-averaged DY of the 200-hPa air temperature in Eurasia ($30^\circ$–$45^\circ$N, $60^\circ$–$105^\circ$E) in November of the previous year, and $X_2$ is the area-average DY of the 200-hPa air temperature in the Atlantic ($30^\circ$–$40^\circ$N, $45^\circ$–$15^\circ$W) in November of the previous year. Both $X_1$ and $X_2$ are related to the NAO. In addition, $X_3$ is the area-average DY of the 200-hPa air temperature south of $60^\circ$S in February of the current year, which is related to the AAO in the Western Hemisphere based on the findings of Wang and Fan (2007) and Fan (2009b). Predictor $X_4$ is the area-average DY of the central Atlantic SLP over the area of $20^\circ$–$30^\circ$N, $30^\circ$–$15^\circ$W in March of the current year, and $X_5$ is the area-average 200-hPa geopotential height over the northwest Pacific ($10^\circ$–$20^\circ$N, $150^\circ$–$165^\circ$E) in April of the current year, which is associated with the intensity of the subtropical high over the Northwest Pacific. Finally, $X_6$ is the area-average 200-hPa zonal wind over the North Pacific ($45^\circ$–$65^\circ$N, $160^\circ$–$120^\circ$W) in April of the current year, which is related to the NPO based on the findings of Wang et al. (2007). The predictors are described in Table 1.

There are two important processes between the predictors and the ATSF. One is the regional atmosphere–ocean process. It is a fact that these six predictors have significantly correlated with the tropical Atlantic SST in the following August–October. The other is the atmospheric teleconnection process. It is also noted that early season predictors would result in the variation of the magnitude of wind vertical shear over the tropical Atlantic in the following August–October through atmospheric teleconnection.

4. A seasonal forecast model for the DY of the ATSF

We used the multiple linear regression method to establish the forecast model (model denoted by M-DY) for the ATSF for the hurricane season, in which M-DY containing six predictors in the form of year-by-year increments was used.

Let $\Delta Y$ stand for the DY of the ATSF and $\hat{Y}(y)$ denote the modeled (observed) ATSF of the current year, while $y_{-1}$ refers to the ATSF of the previous year. We obtain the following DY of the ATSF forecast model in which all of the variables are normalized, and the modeled ATSF is obtained from the modeled DY of the ACTF plus the previous year of the ATSF:

$$
\Delta \hat{Y} = -0.23X_1 + 0.38X_2 + 0.28X_3 - 0.22X_4 + 0.2X_5 - 0.15X_6.
$$

![Fig. 5.](image-url)
The Durbin–Watson statistic tests the residuals from the linear regression or from the multiple regression process independently. The value of the Durbin–Watson statistic of the M-DY is equal to 2.1, which is between the upper and lower critical values at the 0.05 confidence level, indicating no autocorrelation between residuals.

Figure 5 shows that the modeled DY of the ATSF follows well with the interannual variability of the observed DY of the ATSF. The correlation coefficient between the modeled DY of the ATSF and the observed DY of the ATSF during the training period of 1965–99 (35 yr) is 0.85 (0.75), exceeding the 99% significance level and accounting for 72% (56%) of the interyear variance. We note that the DY of the ATSF exhibits remarkable TBO features (Fig. 5a), which supports the hypothesis of the year-by-year incremental approach (Fan et al. 2008).

The simulated and observed ATSFs exhibit reasonable agreement both qualitatively and quantitatively during the period 1965–2009 (Fig. 5b). The forecasting model for the ATSF yields an average root-mean-square error of 2.2, and an average MAE of 1.9 for the years 1965–99. The model successfully simulates the larger variation of the ATSF. Above-normal ATSFs occurred during 14 yr: 1969, 1971, 1984, 1990, 1995, 1996, 1998, 2000, 2001, 2003, 2004, 2005, 2007, and 2008. The MAE is 1.8 in 5 of the above-normal ATSF years (of which there are 14) in which the absolute error is zero; 4 of the years have absolute errors of one, and in 5 of the 14 yr, the absolute error is greater than two (see Table 2).

Below-normal ATSFs occurred during 14 yr: 1967, 1968, 1972, 1973, 1977, 1982, 1983, 1986, 1987, 1991, 1992, 1993, 1994, and 1997, with an MAE of 1.8. In 5 of these 14 yr, the absolute error is one, for 2 of the years, the absolute error is zero, and 5 of these years have absolute errors that are greater than two (see Table 3).

5. Further verification of the model

To compare our work with the work of Klotzbach and Gray (2009), we perform a cross-validation test for the period 1984–2009. For instance, we use the 1965–83 dataset to forecast 1984 values, we use the 1965–2007 dataset to predict the 2008 values, and we employ the 1965–2008 dataset to predict 2009 values. In this way, we have 26 hindcast years derived from 26 equations whose coefficients vary slightly with time, suggesting the stable relationship between the six predictors and the ATSF.

The predicted DY of the ATSF by the cross-validation test fits well with the observed DY of the ATSF, as the correlation coefficient is between the observed DY of the ATSF and the modeled DY of the ATSF, which is 0.87 (0.78) (Fig. 6). The values of the modeled or observed ATSFs and the absolute errors in each year are listed in Table 4.

The M-DY explains the larger interyear variance of the ATSF of 61%, as opposed to 50% according to the work of Klotzbach and Gray (2009), with a smaller MAE of 2.2, rather than 2.96 according to Klotzbach and Gray (2009). Correspondingly, the M-DY has a higher percentage improvement in the MAE of 46% rather than 37% according to the work of Klotzbach and Gray (2009) and compared with the climatology MAE of 4.1 (Table 5).

To verify the prediction skill of the M-DY further, a comparison of the verification of a hindcast for 2004–09 between M-DY and the work of Klotzbach and Gray (2010) was performed. The value of MAE (percentage improvement in MAE) is 2.9 (29%) for the M-DY and 3.5 (15%) for the work of Klotzbach and Gray (2010) (see Table 6).

Therefore, a comparison between the M-DY and the work of Klotzbach and Gray (2009, 2010) indicates the better prediction skill of the M-DY.
6. Comparison with a nondifferenced model

To illustrate further the superior ability of the year-by-year incremental approach in predicting the ATSF, a comparison between the M-DY and a nondifferenced model (M-Y) is performed. The M-Y is also constructed by multilinear regression during 1965–99, which contains the same predictors as those of the M-DY model, but in the original form. It is found that the M-DY shows a better level of predictive skill than does the M-Y. The MAE is 4.1 (2.5) for the M-Y (M-DY) for the ATSF hindcast for 2000–09. When we performed a cross-validation test for the period of 1984–2009, the MAE was 4.1 (2.2) for the M-Y (M-DY), and the percentage improvement was 0 (46%) for the M-Y (M-DY), indicating the superiority of the M-DY (see Table 5).

Elsner and Schmertmann (1993) applied a Poisson regression to develop the seasonal prediction model for intense Atlantic hurricane activity and made a comparison with the model developed by Gray and Landsea (1992) using the linear regression approach. Elsner and Schmertmann (1993) indicated that a nonlinear statistical Poisson regression model was superior to the linear statistical models. Therefore, to explore the prediction ability of the year-by-year incremental approach further, we develop a nonlinear statistical Poisson regression model (M-P) for the ATSF containing the same predictors as those of the M-DY.

The correlation coefficient between the modeled ATSF and the observed ATSF in the M-DY (M-P) is 0.75 (0.66) during the training period 1965–99, accounting for 56% (43%) of the interyear variance. The value of the MAE of the M-DY (M-P) is 1.9 (1.6). The M-DY model has a higher score than does the M-P for the hindcast period 2000–09, with an MAE of 2.5 (4.3) for the M-DY (M-P) (data not shown).

The results of the cross-validation test show that the M-DY is better than the M-P for both the 1984–2009 and 2000–2009 periods, with smaller MAE and higher percentage improvement in MAE. For the period 1984–2009, the values of the MAE (percentage improvement in MAE) are 2.2 (46%) for the M-DY and 3 (27%) for the M-P. For 2000–09, the values of the MAE (percentage improvement in MAE) are 2.4 (41%) for the M-DY and 4.1 (0%) for the M-P (Table 5). The M-DY captures the interannual variability of the observed ATSF better than the M-P does, having a correlation coefficient between the modeled ATSF and the observed ATSF during 1984–2009 of 0.77(0.73) for the M-DY (M-P) (Fig. 6).

7. Discussion and conclusions

In a comparison with the work of Klotzbach and Gray (2009, 2010), the M-DY shows better prediction skill in the cross-validation hindcast for the time period 1984–2009, with a higher correlation coefficient, a smaller MAE, and a higher improvement percentage in the MAE as well (see Tables 4 and 5). In addition, the M-DY exhibits better prediction skill in the verification of hindcasts for 2004–09, with a lower MAE of 2.9, and a higher improvement percentage in the MAE of 29% (see Table 6). The M-DY also has reasonable accuracy for the abnormal ATSF (see Tables 2 and 3). In addition, the M-DY shows...
the best prediction skill among the nondifferenced models (M-Y and M-P) that are constructed on the respective predictors using the multilinear regression and nonlinear Poisson regression.

The advantages of the year-by-year incremental approach may contribute to the good prediction skill of the M-DY when the DY of a variable could capture the TBO feature of a variable and produce an amplified signal, thereby facilitating the capture or identification of marginal changes in the underlying variables. This approach is easy to deal with in the variables, and the trend of a predicted variable is captured by the accumulation of its year-by-year increments.

We consider the ENSO index implicitly in the M-DY due to the complex relationship between the ATSF and ENSO. Because $X_1$, $X_2$, and $X_3$ are significantly correlated with the Niño-3.4 (5°N–5°S, 170°–120°W) SST index of JJASO, the precursors of the ENSO event are contained in the M-DY model. The M-DY model successfully produced an abnormal ATSF for 1997–98 when a warm and cold event of the ENSO phase occurred during the peak of the Atlantic named storm season, and it even successfully reproduced the lowest ATSF in 1983 when a cold event of the ENSO phase occurred in ASO.

It should be noted that there are no true real-time tests for the year-by-year incremental approach, and there are hindcasts in this paper. We will further verify this approach in real-time predictions. It would be interesting to apply this approach to the prediction of Atlantic tropical storm activity, including the intensity, days, tracking, and other circulation systems in which the TBO signal is significant.

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### Table 5. The validation for the cross-validation test during 1984–2009.

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<tr>
<td>MAE (climatology MAE = 4.1)</td>
<td>2.2</td>
<td>2.6</td>
<td>4.1</td>
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<tr>
<td>Improvement in MAE (%)</td>
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<td>37</td>
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### Table 6. The hindcast verification for 2004–2009.

<table>
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<tr>
<th>Year</th>
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<th>M-Y</th>
<th>M-P</th>
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<tr>
<td>2009</td>
<td>9</td>
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MAE (climatology MAE = 4.1) | 2.9 | 3.5 |
Improvement in MAE (%)     | 29  | 15  |

### REFERENCES


