Multi-Year Prediction Model of North Atlantic Hurricane Activity

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Revised to:
Meteorology and Atmospheric Physics

April 8, 1998

Abstract

An empirical prediction algorithm is developed to assess the potential of useful multi-season forecasts of North Atlantic hurricane activity. The algorithm is based on combining separate univariate autoregressive moving average (ARMA) models for each of three dominant components of hurricane activity. A Bayesian criterion is used to select the order of each model. In a single retroactive hindcast experiment, the algorithm is found to make better hindcasts than an ARMA model of the detrended series. A real-time forecast of hurricane activity for the 1997 North Atlantic hurricane season proves to be more accurate than two competitive single-season forecast models. It is expected that the routine use of the forecast algorithm in an operational setting will prove to be only marginally skillful against climatology, it could however offer considerable forecast value as realized by benefits to decision makers in the reinsurance industry.

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1. Introduction

Seasonal forecasts of tropical cyclone activity are now routinely issued for the North Atlantic basin (Elsner *et al.*, 1996a; Gray, 1994) and the Australian region (Nicholls, 1994). Lead time for these forecasts range from less than one month to nearly one year ahead. For example, forecasts of seasonal tropical cyclone activity during July through November for the Atlantic basin are issued in early December of the previous year (Gray *et al.*, 1996; Elsner *et al.*, 1996b). These forecasts are updated in June (Gray *et al.*, 1997), just prior to the beginning of the nearly five-month hurricane season and again in August (Gray *et al.*, 1993; Elsner *et al.*, 1996a) at the start of the peak months (August and September) of the season.

Currently, seasonal tropical cyclone prediction is based entirely on statistical methods. The forecasts provide some beneficial information by determining the likelihood of activity several months in advance with skill. However, their utility for the general public and for industry is limited by several factors. For instance, a forecast of below average tropical cyclone activity in the Atlantic basin may lure coastal residents into a false sense of security since it only takes a single major storm to cause catastrophic losses. An example of this occurred in 1983 as hurricane *Alicia* was an intense U.S. hurricane during a year of below average activity. Seasonal forecasts for specific sub-basins of the North Atlantic attempt to overcome this limitation. Skillful forecast models are possible for the Gulf of Mexico, the Caribbean Sea, and the U.S. southeast coast (Lehmiller *et al.*, 1997).

Another limitation, particularly for the insurance industry is the relatively short lead time of less than one year for the current suite of forecast models. An early December seasonal forecast offers only about 6 to 8 months of lead time. The primary aim of this paper is to demonstrate that this shortcoming can be overcome with the aid of multi-season time-series forecast models of hurricane activity for the Atlantic basin. Lead times are defined as in Barnston *et al.* (1994) to be the time between the end of the latest observed period and the beginning of the predicted period. In this case, if forecasts are issued at the end of the hurricane season then lead times range from 6 months for a single-season forecast to 54 months for a five-season prediction. Within the overall strategy of increased level of precision in the measurement and management of risk, skillful multi-season (long-lead) forecasts would provide reinsurance companies information on liability risk for use in long term financial models.

A recent paper by Elsner *et al.* (1998) demonstrates that important oscillations in the North Atlantic hurricane record are present at the biennial, semi-decadal, and near-decadal time scales.

They employ the method of singular spectrum analysis (SSA) combined with the maximum entropy method (MEM) of fourier analysis. The biennial and semi-decadal oscillations are confined to tropical-only hurricanes, whereas the near-decadal oscillation is restricted to baroclinically-enhanced hurricanes. As a consequence of the distinct power spectra exhibited by these two components of North Atlantic hurricane activity, it is not necessary to separate storm type for the present work. The present work extends the findings of Elsner *et al.* (1998) by using the same methodology to make multi-year predictions of hurricane activity.

The present paper begins with a brief description of the data followed by preliminary analyses, as detailed in Elsner *et al.* (1998). Subsequently, a description of the forecast models including methods of choosing the proper model are provided. The paper ends with a multi-year forecast to the year 2001 in the discussion and summary section.

2. Annual record of North Atlantic hurricanes

The time series of interest is the annual hurricane count for the North Atlantic basin. The North Atlantic basin includes the Atlantic Ocean north of the equator, the Caribbean Sea, and the Gulf of Mexico. The hurricane season runs from June through November with a majority of hurricanes occurring during the months of August and September. In fact, 66% of Atlantic basin hurricane activity over the period 1900–96 occurred during these two months. The annual hurricane count is extracted from the National Hurricane Center's best-track data set. The data set is also known by the acronym HURDAT for HURricane DATa. Annual counts are available back to 1886 but are more reliable after the middle 1940's when the U.S. Air Force began aircraft reconnaissance missions to investigate individual storms.

The present study considers the annual counts from 1886 through 1996 as a univariate time series. Original data sources and issues of data accuracy are discussed in Neumann *et al.* (1993). The effect of slightly fewer number of recorded hurricanes over the earliest years compared with the more recent years is partially ameliorated by removing the trend before analysis as explained in section four. Before any analysis is performed, the hurricane record is normalized by subtracting the mean from each year's number of hurricanes and dividing by the standard deviation (where the base period for the mean and standard deviation is the entire record from 1886 through 1996).

3. Preliminary analysis

The analysis begins by considering the lagged-covariance matrix ($\mathbf{S}$) of the univariate time series $x(t)$ computed as

$$S_{ij} = \frac{1}{N_t - m + 1} \sum_{t=1}^{N_t - m + 1} x(i + t - 1)x(j + t - 1). \tag{1}$$

This method was original used by Broomhead and King (1986). The eigenvectors of $\mathbf{S}$ can be used to compute the principal components (a^k's) by projecting the original time record onto them as follows

$$a_i^k = \sum_{j=1}^{m} x(i + j - 1)e_j^k, \tag{2}$$

for $i = 1, 2, \ldots, N$, where e_j^k represents the jth component of the kth eigenvector. With the normalization used above, the variance of each principal component is λ_k and the amplitudes increase with increasing k. As a result of orthogonality, each principal component can be isolated and probed independently from the remainder of the time record. The principal components are used to reconstruct all or a selected portion of the time series. These reconstructed components, computed as

$$x(i + j - 1) = \sum_{k=1}^{m} a_i^k e_j^k, \tag{3}$$

are not pure waves but are limited in harmonic content. Since the time series is a sum of all individual reconstructed components, the removal of one or more components is a form of filtering. The prediction algorithm described below involves building individual models separately for each of the important reconstructed components.

However, before predictions are attempted trends or ultra-low frequency components in the time series are removed. The original time series consists of annual hurricane counts for the Atlantic basin for the period 1886–1996 (Figure 1). For this time series, trends and extremely low frequency oscillations can arise from changes in observing techniques over the years and from natural fluctuations, perhaps induced by changes in sea surface temperatures. Following Vautard *et al.* (1992), the SSA can be used as part of an algorithm for removing trends which also includes the non-parametric test of Kendall and Stuart (1977). This method is used in Elsner *et al.* (1998) to detrend the annual hurricane record. The detrended record is shown in Figure 2. For the remainder of the paper we concentrate only on the detrended record.

The preliminary analysis continues by extracting the dominant oscillations in the detrended record. This is done in Elsner *et al.* (1998) according to Eq. (3). Figure 3 shows the reconstructed components from the three dominant eigenvector pairs. Although these components indicate irregular oscillations (i.e., they are not pure waves), there is a distinct oscillation to each of them. The reconstructed component from the first eigenvector pair indicates a semi-decadal oscillation. The reconstructed component from the second eigenvector pair indicates a high frequency (biennial) oscillation while the reconstructed record from the third pair suggests a lower frequency sub-decadal oscillation. The reconstructed components, although having limited harmonic content show amplitude modulation with different frequencies dominating the total variability (sum of the reconstructed components) during different epochs. For example, during the 1950's and 60's the biennial oscillation is relatively robust compared with the sub-decadal variability while during the middle 1980's until present, the biennial component is somewhat less important.

The 2.5-year periodicity reflects the well-established association of hurricane activity with the stratospheric quasi-biennial oscillation (QBO), while the semi-decadal oscillation is likely tied to the El Niño - Southern Oscillation (ENSO) of the Pacific basin, which has an irregular fluctuation in the range of 4 to 6 years and has been implicated in modulating major hurricane activity in the North Atlantic basin. Observational and modeling studies independently confirm this linkage, which is probably related through increased vertical shear of the horizontal winds over prime hurricane genesis regions of the North Atlantic (Goldenberg and Shapiro, 1996). More speculative, the sub-decadal oscillation might be induced by long-period changes in sea surface temperatures in parts of the North Atlantic Ocean (Landsea *et al.*, 1994). For example, Kimberlain and Elsner (1998) show that sea surface temperatures in a region to the east of the Lesser Antilles appears to modulate hurricane activity with more tropical-only hurricanes (Elsner *et al.*, 1996c) occurring during warm years. The warm and cold years appear to alternate on the time scale of 7 to 10 years.

4. Forecast models

Due to the restricted harmonic content, the reconstructed components are readily amenable to low-order autoregressive modeling. Let $\{x(t)\}$ be the detrended hurricane series for the North Atlantic basin, and denote the three dominant reconstructed components of the detrended hurricane series by $\{y_1(t)\}$, $\{y_2(t)\}$ and $\{y_3(t)\}$. In this section, univariate autoregressive moving average (ARMA) models will be built for the four series for the purpose of forecasting. In general, a time series $\{y(t)\}$ may be modeled as an ARMA(p, q) model with the form:

$$y(t) - \phi_1 y(t-1) - \cdots - \phi_p y(t-p) \quad = \quad \mu + \epsilon(t) - \theta_1 \epsilon(t-1) - \cdots - \theta_q \epsilon(t-q), \tag{4}$$

where the $\epsilon(t)$'s are assumed to be independent and normally distributed with mean zero and variance σ^2. In the model, p is the order of the autoregression (AR) term, and q is the order of the moving-average (MA) term. The AR and MA coefficients in the model will be denoted by $\boldsymbol{\phi} = (\phi_1, \ldots, \phi_p)'$ and $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_q)'$, respectively. If some coefficients in model (4) are zeros, i.e., $\phi_i = 0$ for $i < p$ or $\theta_j = 0$ for $j < q$, then model (4) is called a parsimonious ARMA(p, q) model.

The first step of modeling a time series is to identify a tentative model for the data set. Numerous criteria have been proposed for model selection in time series literature (see, e.g., Box and Jenkins, 1976; Brockwell and Davis, 1991). For example, Schwartz (1978) suggested a Bayesian criterion (SBC), which is similar to Akaike's Bayesian criterion (BIC). Specifically, assume that an ARMA(p, q) model of M parameters is fitted to a data set. Then the SBC for the fitted model is defined as

$$SBC(M) \quad = \quad -2\log(L(\hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\theta}}, \hat{\sigma}^2) + M\log(n), \tag{5}$$

where $L(\hat{\boldsymbol{\phi}}, \hat{\boldsymbol{\theta}}, \hat{\sigma}^2)$ is the maximum of the likelihood function for the parameters, and n is the sample size. Among a group of adequate models to fit the data set, the one with the smallest SBC value will be selected as the best choice.

Since the time-series models require continuous records, the skill assessment of cross-validation (Michaelson, 1987; Elsner and Schmertmann, 1993) can not be directly implemented here. To estimate forecast skill the retroactive method is used. The retroactive method requires the model be built from data over a portion of the record and hindcasts be made on the remaining withheld portion. The cut point between building and hindcasting represents a compromise between model integrity and skill assessment. If the cut is made so that half is used for training and half for hindcasts then the model is very sensitive to the earliest part of the record, but good statistics can be made for accurate skill assessment. On the other hand, if the cut is made to maximize the number of years used to build the model, then skill assessment is limited. Since the record is only 96 values long, it is imperative to use most of the record for building the model at the expense of only a token assessment of skill. However, the uncertainty of the hindcasts are treated.

A univariate ARMA(p, q) model is built for each of the four series by using the first 91 observations in the series (1901–1991). The Schwartz Bayesian criterion is used for model selection and the maximum likelihood method is used to estimate the parameters in the chosen model. The final chosen model for $\{y_1(t)\}$, the first dominant reconstructed component of the the detrended hurricane series, is a parsimonious AR(15) model with the form:

$$\begin{aligned} y_1(t) \quad &= \quad \phi_1 y_1(t-1) + \phi_2 y_1(t-2) + \phi_3 y_1(t-3) + \phi_6 y_1(t-6) + \phi_9 y_1(t-9) \\ &\quad +\phi_{10} y_1(t-10) + \phi_{11} y_1(t-11) + \phi_{13} y_1(t-13) \end{aligned}$$

$$+\phi_{15}y_1(t-15)+\epsilon(t). \qquad (6)$$

The estimated parameters along with the estimated standard errors are listed in Table 1. In the table, the R^2 for the fitted model is calculated by the formula:

$$R^2 = 1-\frac{\sum_{t=1}^{n}(y_1(t)-\hat{y}_1(t))^2}{\sum_{t=1}^{n}(y_1(t)-\bar{y}_1)^2},$$

where $\{\hat{y}_1(t), t=1,\ldots,n\}$ are the fitted values based on the model. The value of $R^2=0.81$ means that the parsimonious AR(15) model explains about 81% of the total variation of the series $\{y_1(t)\}$.

The final identified model for the second dominant reconstructed component $\{y_2(t)\}$ is the following parsimonious ARMA(15, 2) model:

$$\begin{aligned} y_2(t) &= \phi_1 y_2(t-1)+\phi_2 y_2(t-2)+\phi_4 y_1(t-4)+\phi_{10}y_1(t-10) \\ &\quad +\phi_{13}y_1(t-13)+\phi_{15}y_1(t-15)+\epsilon(t)-\theta_2\epsilon(t-2). \qquad (7)\end{aligned}$$

The estimated parameters and the estimated standard errors are listed in Table 2, in which the value of $R^2=0.72$ indicates that about 72% of the total variation of the second dominant component of the detrended hurricane series is explained by the fitted model.

The third dominant reconstructed component $\{y_3(t)\}$ has much smaller variation than the first two components (Figure 3). The final fitted model for this series is an AR(8) model, i.e.,

$$y_3(t) = \sum_{i=1}^{8}\phi_i y_3(t-i)+\epsilon(t). \qquad (8)$$

The estimated coefficients in this model are given in Table 3, and about 83% of the total variation of this series is explained by the fitted AR(8) model.

Similarly, a time series model is fitted to $\{x(t)\}$ by using 91 observations of the detrended hurricane series over the period from 1901 to 1991. The final identified model for this series is the following parsimonious AR(17) model:

$$x(t) = \phi_{10}x(t-10)+\phi_{17}x(t-17)+\epsilon(t). \qquad (9)$$

The estimated coefficients are $\hat{\phi}_{10}=0.238$ and $\hat{\phi}_{17}=0.276$ with estimated standard errors of $\mathrm{se}(\hat{\phi}_{10})=0.101$ and $\mathrm{se}(\hat{\phi}_{17})=0.104$, respectively. The R^2 for this fitted model is 0.10, which means that only 10% of the total variation of the detrended hurricane series is explained by the fitted model. This model, although very limited in terms of predictability, is clearly better than white noise as indicated by the SBC.

Based on the R^2 values of the fitted univariate time series models for the four series, it is clear that each of the three dominant reconstructed components can be well fitted by an ARMA(p, q) model but not the detrended hurricane series itself. The fitted models for the three components are used to forecast (hindcast) values over the next 5 years (1992–96). The five-year real and forecast values of the three dominant components are listed in Table 4 along with lower and upper bounds of the 95% confidence intervals.

It is notable from Table 4 that all of the real values are within their 95% confidence intervals. Except for a few extreme cases such as the 1995 value of the first component and the 1994 value of the second component, the forecast values are quite close to their corresponding actual values (based on the detrended series). The third dominant component appears to be more accurately predicted by its fitted model than other two components, which is partially due to smaller variability of this series. Figure 4 shows the hindcasts in terms of the actual numbers of hurricanes. The model appears to do well in predicting the upswing in hurricane activity between 1994 and 1995, though the uncertainty is large and grows with lead time.

5. Discussion and summary

In this study the annual abundance of North Atlantic hurricanes is examined from the perspective of time series prediction. The time series analysis is done using the procedures of SSA and MEM as described in Elsner *et al.* (1998). The annual number of North Atlantic hurricanes is first detrended to remove the ultra-low frequency components and trends of the historical data set. Such components can arise due to the known improvements in our ability to accurately log all hurricane occurrences over the period and from natural variability, perhaps forced by long-period changes in SSTs.

After detrending, the dominant reconstructed components from an SSA reveal important modes of Atlantic basin hurricane variability at the biennial, semi-decadal and sub-decadal time scales. The high frequency component is consistent with the stratospheric QBO (28–31 months) and its known impact on hurricane activity (Gray, 1984). The semi-decadal oscillation, which accounts for the greatest percentage of time-series variance, is likely related to the ENSO of the tropical Pacific basin. Recent studies (Gray, 1984; Gray *et al.*, 1993; Goldenberg and Shapiro, 1996) have shown a teleconnection between ENSO and Atlantic hurricane abundance, with a warm ENSO phase associated with fewer storms and a cold ENSO phase with more storms. It is suggested by numerous authors that the linkage is likely related to changes in upper-tropospheric flow. The sub-decadal oscillation might be tied to low frequency changes in Atlantic SST changes, which could be linked to solar activity (Elsner and Kara, 1998).

An empirical prediction algorithm is designed to examine the potential for useful multi-season forecasts of Atlantic basin hurricane activity. The algorithm requires separate ARMA models for each of the three dominant reconstructed components in the detrended record. A modified Bayesian criteria is used to select the proper order of the autoregressive and moving-average component for each model. The in-sample R^2 values indicate that the models are capable of explaining between 72 and 83% of the total variation in the reconstructed components. The models are developed on data over the period 1901–91, inclusive. A hindcast prediction for the years 1992–96 shows that the algorithm is better at forecasting the individual components separately compared with using an ARMA model to forecast the detrended record itself (in this case the R^2 value is 0.10). The method appears to do well in hindcasting above normal activity for the vigorous 1995–96 period (20 Atlantic basin hurricanes). Standard error calculations indicate a large uncertainty in predicted numbers that grows with lead time, as expected.

Formal statistical significance in the validation of time-series models with limited data is difficult to calculate. We have provided a fair test against an ARMA model on the detrended record for a limited five-year (1992–96) case study. Yet it should be kept in mind that over the span of these five years the hurricane abundance went from well-below (1992–94) to well-above (1995–96) the long-term average so the limited case study spans the spectrum of Atlantic basin hurricane variability. Although the comparison between the two approaches is fair, a few caveats are important. First, since the sum of the three reconstructed components explains about 60% of the detrended series, even an algorithm capable of forecasting 80% of the reconstructed record is, in effect, only explaining about 50% of the actual detrended record. Furthermore, since the reconstruction is based on the entire period (1886–1996) the hindcast skill is not from totally independent information. Note, however, this is also true to some extent of the hindcast evaluation of the ARMA model of the detrended record since the detrending was done using all the data. Nevertheless, based on the clear advantage of modeling the components separately and on results using similar modeling strategies (Jiang *et al.*, 1996; Keppenne and Lall, 1996), confidence is high that this approach is sound.

To further demonstrate the likely skill of this approach, a real-time forecast is made in operational mode. Using the methodology described above a five-season forecast for the years 1997 through 2001 is made. Model parameters are estimated based on data over the period 1886–1996. Note this forecast involves no look-ahead information as the model is initialized with data only through the 1996 North Atlantic hurricane season. Table 5 shows the forecast and associated error bounds. Also included are single-season forecasts from the Colorado State University group and our group at Florida State University issued in December of 1996 and December of 1997. Both the single-season forecast models are multiple regression models involving various predictors. The multi-year model predicted 4 hurricanes for the 1997 season. This compares with early December 1996 forecasts of 7 and 6 hurricanes based on the two regression models. The actual number of hurricanes over the North Atlantic for 1997 was 3. Although the multi-year model out-performed the two single-season models, caution is advised as this is a single comparison and will not likely generalize over all years. This caveat is important in light of the failed forecast of a La Niña event given by Keppenne and Ghil (1992). The model indicates below average hurricane activity for 1998, but above average activity in the year 2000. The below average activity forecast for 1998 is consistent with the early December 1997 single-season forecast model projections. Note should be made of the fact that the trend is not replaced in the forecast values. We will continue this kind of real-time verification of the multi-year hurricane forecast model.

Although it is likely that the skill level of the multi-year model when used in an operational mode over the long run will only be marginal against climatology, the extended lead time offers additional benefits to risk management. Multi-year predictions are valuable to calculating insured risk by allowing for modification of the probabilities incorporated within existing risk models (RPI, 1997). This study will be extended to investigate the potential of using the methodology to make useful multi-year projections of intense hurricane activity and U.S. landfalling hurricane activity. Additionally, research into the connection between North Atlantic SSTs and hurricanes could lead to the development of space-time multi-year forecast models. Research along these lines is also continuing.

Acknowledgements: The constructive criticism of the two reviewers have made for a tighter, more readable paper. Some support for this work came from NOAA through the Cooperative Institute on Tropical Meteorology (CITM), the National Science Foundation (NSF) ATM-9417528 and ATM-9618913, and the Risk Prediction Initiative (RPI) of the Bermuda Biological Station for Research (BBSR).

References

1. Barnston, A., and Coauthors, 1994: Long-lead seasonal forecasts–where do we stand? *Bulletin of the American Meteorological Society*, **75**, 2097–2114.

2. Box, G.E.P. and Jenkins, G.M., 1976: *Time Series Analysis: Forecasting and Control,* Holden-Day Inc, 575 pp.

3. Brockwell P.J. and Davis, R.A., 1991: *Time Series Theory and Methods.* Second Edition, Springer-Verlag, New York, 519 pp.

4. Broomhead, D.S. and King, G.P., 1986: Extracting qualitative dynamics from experimental data. *Physica D*, **20**, 217–236.

5. Elsner, J.B., and Schmertmann, C.P., 1993: Improving extended-range seasonal predictions of intense Atlantic hurricane activity. *Weather and Forecasting*, **8**, 345-351.

6. Elsner, J.B., Lehmiller, G.S., and Kimberlain, T.B., 1996a: Early August forecasts of Atlantic tropical storm activity for the balance of the 1996 season, using Poisson models. *Experimental Long-lead Forecast Bulletin*, **5**(3), 26–28.

7. Elsner, J.B., Lehmiller, G.S., and Kimberlain, T.B., 1996b: Forecast of Atlantic tropical storm activity for 1997. *Experimental Long-lead Forecast Bulletin*, **5**(4), 34–36.

8. Elsner, J.B., Lehmiller, G.S., and Kimberlain, T.B., 1996c: Objective classification of Atlantic hurricanes. *Journal of Climate*, **9**, 2880–2889.

9. Elsner, J.B., Kara, A.B., and Owens, M.A., 1998: Fluctuations in North Atlantic hurricane activity. *Journal of Climate*, **11**, in press.

10. Elsner, J.B., and Kara, A.B., 1998: *Hurricanes of the North Atlantic: Climate and Society*, Oxford University Press, 500 pp.

11. Goldenberg, S.B., and Shapiro, L.J., 1996: Physical mechanisms for the association of El Niño and west African rainfall with Atlantic major hurricane activity. *Journal of Climate*, **9**, 1169–1187.

12. Gray, W.M., 1984: Atlantic seasonal hurricane frequency: Part II: Forecasting its variability. *Monthly Weather Review*, **112**, 1669–1683.

13. Gray, W.M., Landsea, C.W., Mielke Jr., P.W., and Berry, K.J., 1993: Predicting Atlantic basin seasonal tropical cyclone activity by 1 August. *Weather and Forecasting*, **8**, 73–86.

14. Gray, W.M., 1994: LAD multiple linear regression forecasts of Atlantic tropical storm activity for 1995. *Experimental Long-lead Forecast Bulletin*, **3**(4), 12–13.

15. Gray, W.M., Landsea, C.W., Mielke, P.W., Berry, K., and Knaff, J., 1996 LAD multiple linear regression forecasts of Atlantic tropical storm activity for 1997. *Experimental Long-lead Forecast Bulletin*, **5**(4), 37–40.

16. Gray, W.M., Landsea, C.W., Mielke, P.W., Berry, K., and Knaff, J., 1997 LAD multiple linear regression forecasts of Atlantic tropical storm activity for 1997. *Experimental Long-lead Forecast Bulletin*, **6**(2), 52–54.

17. Jiang, N., Ghil, M., and Neelin, J.D. 1996: Forecasts of Niño 3 SST anomalies and SOI based on singular spectrum analysis combined with the maximum entropy method. *Experimental Long-lead Forecast Bulletin*, **5**(2), 51–53.

18. Keppenne, C. L. and Ghil, M. 1992: Extreme weather events. *Nature*, **358**, 547.

19. Keppenne, C. L. and Lall, U., 1996: Complex singular spectrum analysis and multivariate adaptive regression splines applied to forecasting the southern oscillation. *Experimental Long-lead Forecast Bulletin*, **5**(2), 54–56.

20. Kendall, M.G. and Stuart, A., 1977: *The Advanced Theory of Statistics*, Griffin, London, 4th ed., 455 pp.

21. Kimberlain, T.B. and Elsner, J.B., 1998: The 1995 and 1996 North Atlantic hurricane seasons: A return of the tropical-only hurricane. *Journal of Climate*, **11**, in press.

22. Landsea, C. W., Gray, W. M., Mielke, P. W., and Berry, K. J., 1994: Seasonal forecasting of Atlantic hurricane activity. *Weather*, **49**, 273-284.

23. Lehmiller, G.S., Kimberlain, T.B., and Elsner, J.B., 1997: Seasonal prediction models for the North Atlantic basin hurricane location. *Monthly Weather Review*, **125**, 1780–1791.

24. Neumann, C.J., Jarvinen, B.R., McAdie, C.J., and Elms, J.D., 1993: *Tropical Cyclones of the North Atlantic Ocean, 1871–1992*, NOAA Historical Climatology Series 6–2, 193 pp.

25. Nicholls, N., 1994: SOI-based forecast of Australian region tropical cyclone activity. *Experimental Long-lead Forecast Bulletin*, **3**(4), 16–17.

26. Michaelsen, J., 1987: Cross-validation in statistical climate forecast models. *J. Clim. Appl. Meteor.*, **26**, 1589–1600.

27. Risk Prediction Initiative, 1997: *Tropical Cyclones and Climate Variability: A Research Agenda for the Next Century.* Ed. Malmquist, D. L., Bermuda Biological Station for Research, 46 pp.

28. Schwartz, G., 1978: Estimating the dimension of a model, *The Annals of Statistics*, **6**, 461–464.

29. Vautard, R., Yiou, P., and Ghil, M., 1992: Singular spectrum analysis: a toolkit for short, noisy and chaotic series. *Physica D*, **58**, 95–126.

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Table 1. Estimated coefficients and the estimated standard errors for the model of the first reconstructed component.

Coefficient	Estimates	Std Error	t-Ratio
ϕ_1	0.372	0.082	4.54
ϕ_2	-0.508	0.081	-6.27
ϕ_3	-0.446	0.102	-4.37
ϕ_6	-0.325	0.109	-2.98
ϕ_9	-0.246	0.104	-2.37
ϕ_{10}	0.371	0.092	4.03
ϕ_{11}	-0.282	0.093	-3.03
ϕ_{13}	-0.252	0.098	-2.58
ϕ_{15}	-0.300	0.082	-3.66
R^2	0.81		

Table 2. Estimated coefficients and the estimated standard errors for the model of the second reconstructed component.

Coefficient	Estimates	Std Error	t-Ratio
ϕ_1	-0.639	0.077	-8.30
ϕ_2	-0.312	0.085	-3.67
ϕ_4	-0.421	0.068	-6.19
ϕ_{10}	0.355	0.087	4.08
ϕ_{13}	-0.227	0.065	-3.49
ϕ_{15}	-0.253	0.075	3.37
θ_2	0.487	0.110	4.43
R^2	0.72		

Table 3. Estimated coefficients and the estimated standard errors for the model of the third reconstructed component.

Coefficient	Estimates	Std Error	t-Ratio
ϕ_1	1.023	0.104	9.85
ϕ_2	−1.099	0.148	−7.43
ϕ_3	0.425	0.173	2.46
ϕ_4	−0.836	0.165	−5.07
ϕ_5	0.578	0.163	3.55
ϕ_6	−0.834	0.167	−4.99
ϕ_7	0.367	0.152	2.41
ϕ_8	−0.273	0.112	−2.44
R^2	0.83		

Table 4. The five-year normalized detrended values, hindcast values, lower and upper bounds of the 95% confidence intervals for the hindcast values of the three dominant reconstructed components.

Year	Normalized	Hindcast	Lower bound	Upper bound
		The first dominant component		
1992	−1.156	−0.835	−1.362	−0.308
1993	−0.480	−0.457	−1.020	0.105
1994	0.353	0.138	−0.457	0.733
1995	1.739	1.102	0.381	1.823
1996	0.565	0.384	−0.350	1.119
		The second dominant component		
1992	0.243	0.232	−0.183	0.646
1993	−0.053	−0.208	−0.700	0.284
1994	−0.501	−0.101	−0.619	0.416
1995	0.323	0.110	−0.440	0.660
1996	−0.178	−0.254	−0.855	0.348
		The third dominant component		
1992	−0.236	−0.288	−0.404	−0.172
1993	−0.212	−0.297	−0.464	−0.130
1994	−0.136	−0.166	−0.333	0.001
1995	−0.028	−0.034	−0.223	0.154
1996	0.051	0.112	−0.117	0.341

Table 5. A five-year forecast initialized in June of 1997 using ARMA models on the reconstructed components from a SSA. Also included are the single-season forecasts issued in December of 1996 and December of 1997.

Year	Forecast	Error	CSU	FSU	Actual
1997	4.4	±3.1	7	6	3
1998	2.8	±3.3	5	3	–
1999	3.4	±3.3	–	–	–
2000	6.7	±3.4	–	–	–
2001	6.4	±3.5	–	–	–

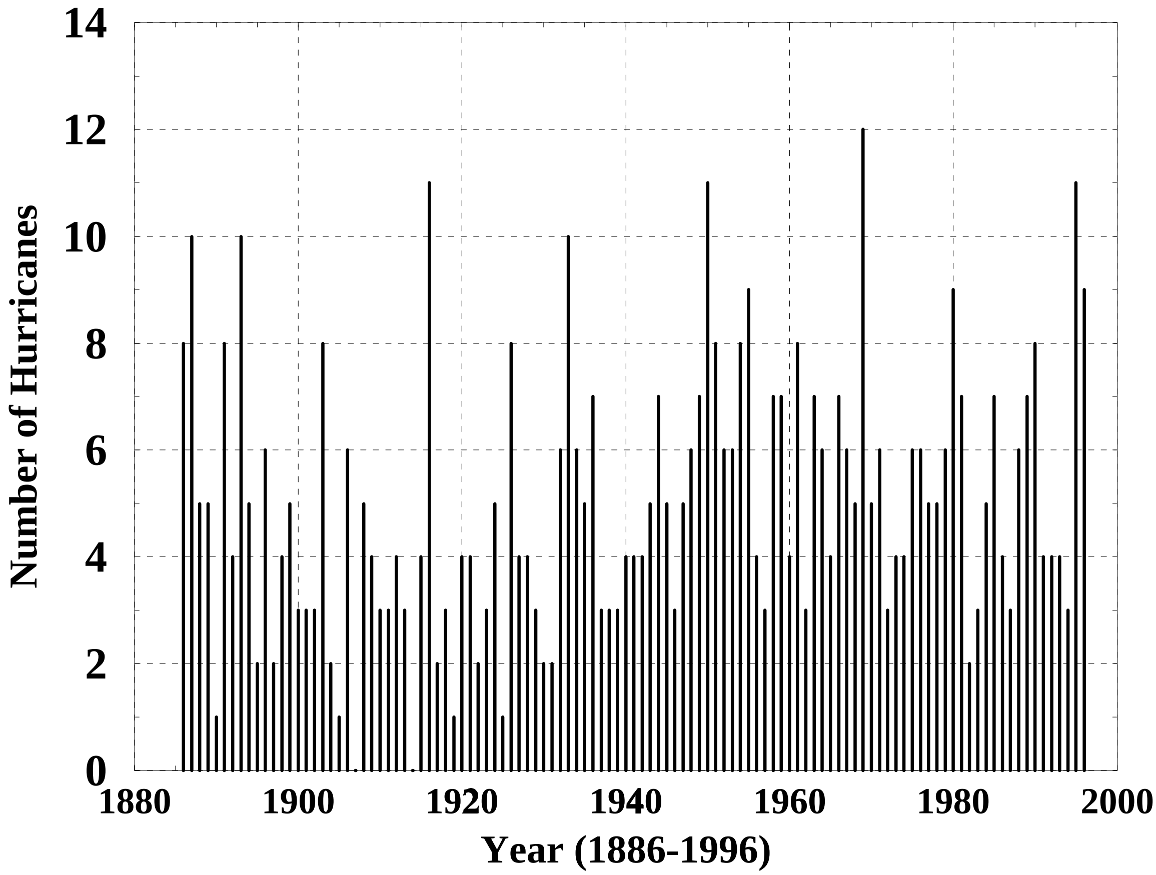


Figure 1: Time series of the total number of North Atlantic basin hurricanes from 1886–1996 based on the best-track data set.

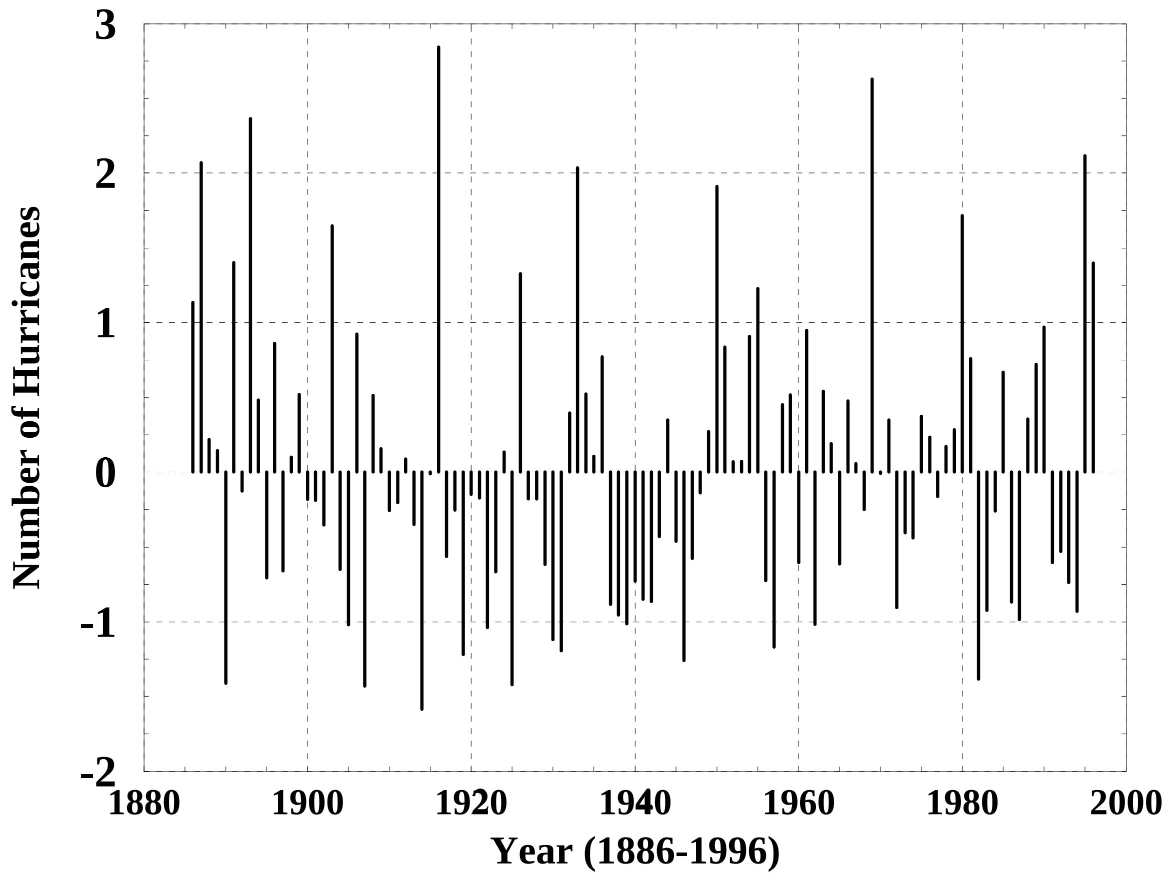
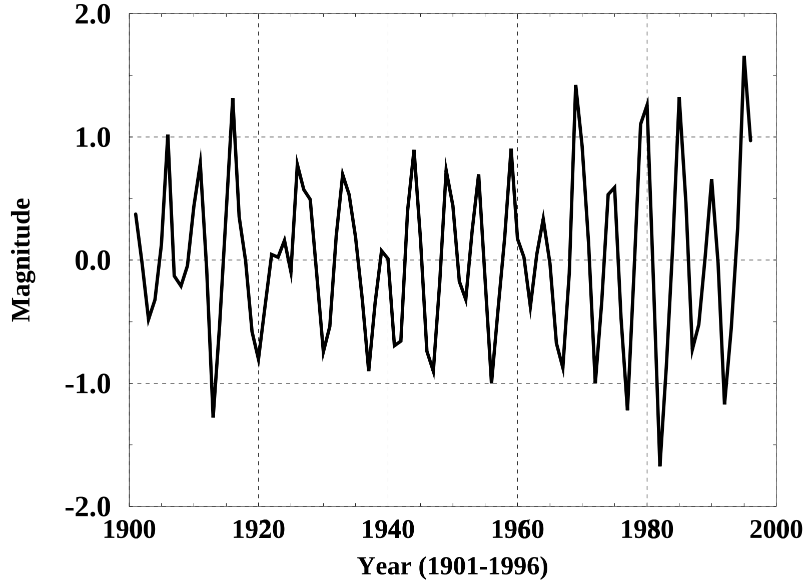
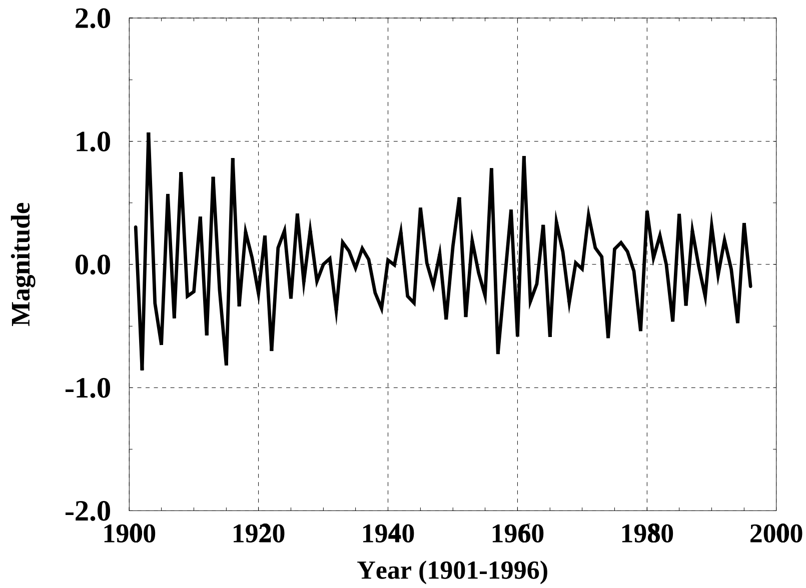


Figure 2: Detrended time series of the total number of North Atlantic basin hurricanes. The series is detrended by removing the leading ultra low-frequency temporal eigenvector, after Elsner *et al.* (1998).


2.0
1.0
0.0
-1.0
-2.0
Magnitude
1900
1920
1940
1960
1980
2000
Year (1901-1996)


2.0
1.0
0.0
-1.0
-2.0
Magnitude
1900
1920
1940
1960
1980
2000
Year (1901-1996)

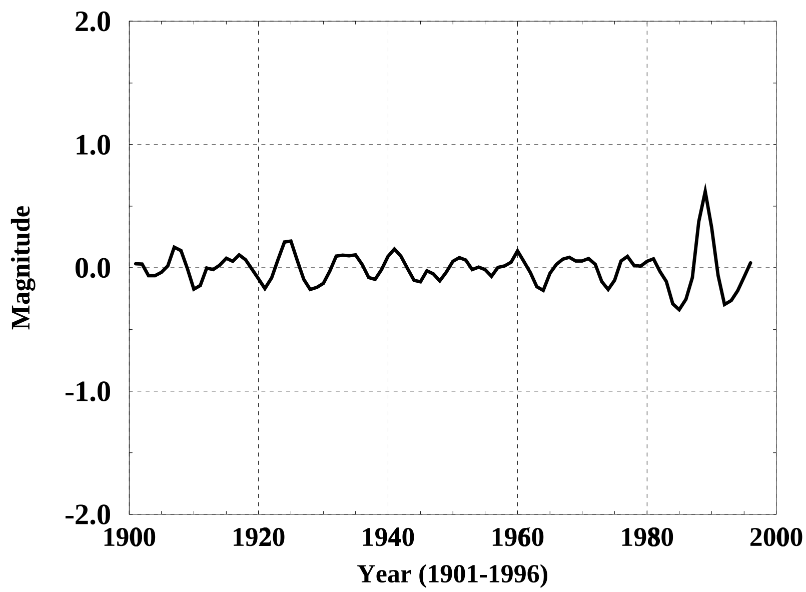


Figure 3: The three dominant reconstructed components of the detrended hurricane record using the method of SSA. Each reconstructed record corresponds to a distinct oscillation with limited harmonic content (see Elsner *et al.* 1998).

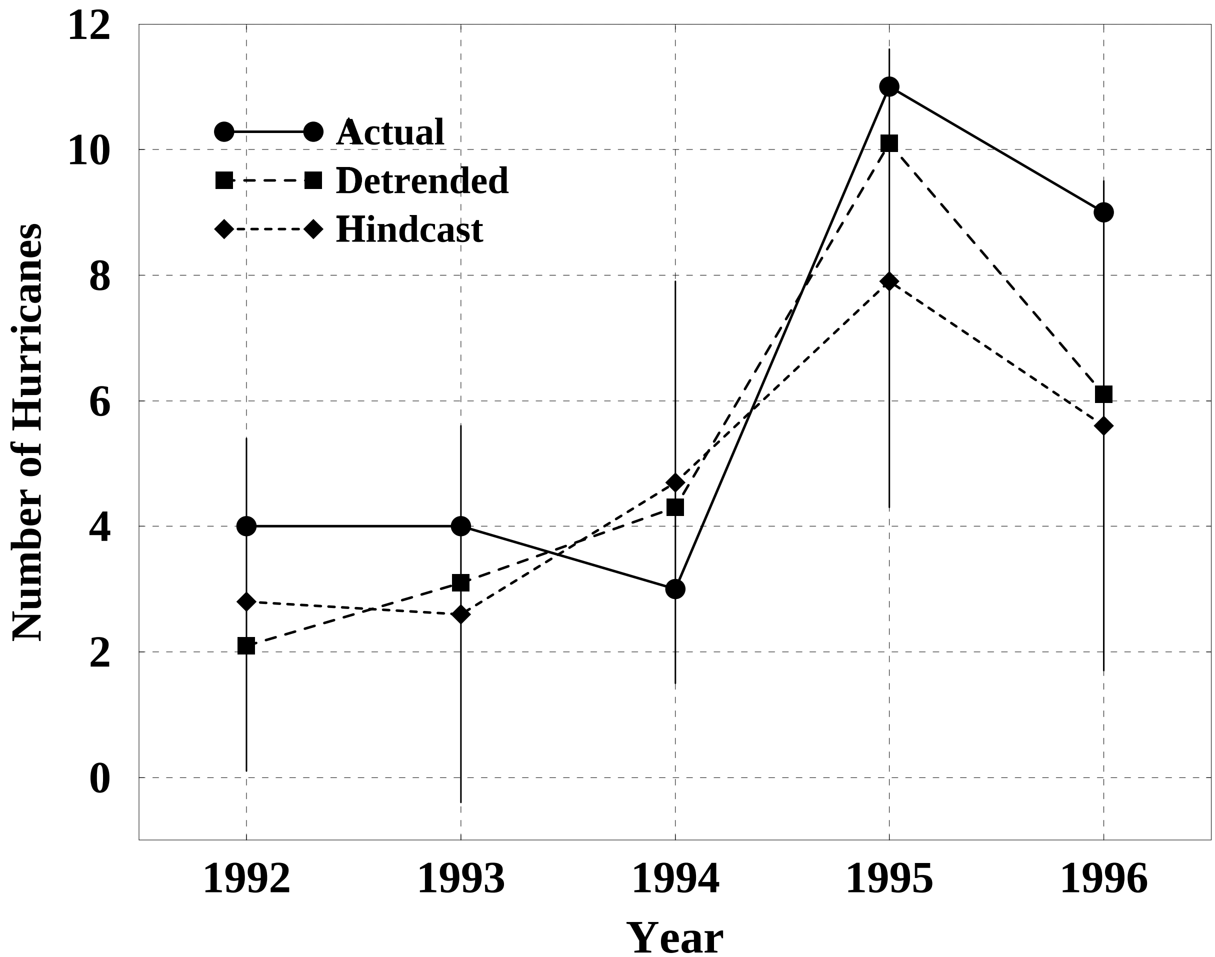


Figure 4: Hindcasts of annual North Atlantic hurricane abundance in the five-year period 1992–96 expressed in terms of actual number of storms The detrended values along with the lower and upper bounds of the 95% confidence intervals for the hindcast values are also shown.