Low-Frequency Modulation of the ENSO–Indian Monsoon Rainfall Relationship: Signal or Noise?

ALEXANDER GERSHUNOV, NIKLAS SCHNEIDER, AND TIM BARNETT

Climate Research Division, Scripps Institution of Oceanography, University of California, San Diego, La Jolla, California

21 August 2000 and 31 December 2000

ABSTRACT

Running correlations between pairs of stochastic time series are typically characterized by low-frequency evolution. This simple result of sampling variability holds for climate time series but is not often recognized for being merely noise. As an example, this paper discusses the historical connection between El Niño–Southern Oscillation (ENSO) and average Indian rainfall (AIR). Decades of strong correlation (~ -0.8) alternate with decades of insignificant correlation, and it is shown that this decadal modulation could be due solely to stochastic processes. In fact, the specific relationship between ENSO and AIR is significantly *less* variable on decadal timescales than should be expected from sampling variability alone.

1. Introduction

Running correlation analysis, that is, correlations computed in moving windows, is frequently used in climate research to diagnose changes in relationships between two indices. This paper discusses the dangers of physically interpreting low-frequency variability in running correlations, particularly between indices of interannual modes of climate variability. As an example, we focus on a relationship whose changing nature has been the topic of recent scientific concern, a relationship of great societal importance, and historical significance in the annals of climatology: the relationship between the Indian monsoon rainfall and El Niño–Southern Oscillation.

The strength of the Southern Oscillation–Indian monsoon rainfall relationship during the late 1800s and early 1900s led Sir Gilbert Walker to discover the Southern Oscillation (SO; Walker 1924; Walker and Bliss 1932). The next several decades witnessed a general breakdown in the SO–Indian rainfall connection and curiosity about SO went into hibernation until it was reawakened by the strong Niño of 1957–58 and vigorous El Niño activity in the 1960s (see Wallace et al. 1998). El Niño–Southern Oscillation (ENSO) is now widely regarded as an influence on Indian rainfall (Webster et al. 1998, and references therein). As we shall see, renewed interest in the ENSO–average Indian rainfall (AIR) connection is due, in part, to its renewed strength in the late 1960s and 1970s and to its apparent breakdown since then.

The decadal variation, or apparent nonstationarity, of the ENSO–AIR relationship has been considered by Pant et al. (1988) and more recently by Krishnamurthy and Goswami (2000), Mehta and Lau (1997), and by Krishna Kumar et al. (1999a,b). All of these studies employed running correlation analysis and attempted to relate changes in AIR to physical causes. Pant et al. (1988) and Krishnamurthy and Goswami (2000) focus on the decadal variability in AIR and offer explanations involving natural modes of low-frequency climate variability. Meta and Lau (1997) attribute similar variability in AIR to the influence of solar irradiance. Krishna Kumar et al. (1999a,b), on the other hand, claim that AIR has been stable through history but has experienced a breakdown in recent decades due to effects of global warming.[1]

In what follows, we show that the waxing and waning of the ENSO–AIR relationship is a recurrent phenomenon with interdecadal timescales. We show that the

Corresponding author address: Alexander Gershunov, Climate Research Division, Scripps Institution of Oceanography, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093-0224.
E-mail: sasha@ucsd.edu

[1] Such studies are important for ongoing efforts to predict interannual AIR variability using statistical predictors. Curiously, ENSO is usually considered one of the most important predictors despite the fact that AIR leads ENSO (Normand 1953; Yasunari 1990; and Fig. 1a, this paper). Statistical forecasting efforts have traditionally met with only intermittent success (see Webster et al. 1998; Krishna Kumar et al. 1995), prompting deep questions into the nature of the ENSO–AIR connection as in, for example, Webster et al. (1998).

relationship between ENSO and a spatially broader rainfall index of the Asian monsoon is also characterized by very strong decadal modulation. Furthermore, the two Asian monsoon indices are themselves inconsistently related. We present evidence that this type of low-frequency modulation is common to pairs of time series derived from noise processes, so that the physics of the relationship need only be stochastic in character. A statistical test reveals that the level of such stochastic modulation of the ENSO–AIR relationship is significantly lower than should be expected by chance.

2. Results

a. ENSO–AIR Relationship (EAR)

Both eastern and western tropical Pacific monthly SST anomalies display strongest correlations with AIR at considerable lags. Yasunari (1990) estimates maximum correlations with SST in the January and February following the June–September AIR. Figure 1a shows the evolution of the correlation between AIR and monthly Niño-3.4 (SST averaged over 5°S–5°N, 170°–120°W). Based on our 124-yr observational record, maximum correlations ($r \approx -0.6$) occur in August–November, remaining strong and stable until March of the following year. June–July, however, is a transitional period when the ENSO–AIR relationship is beginning to assert itself as evidenced by rapidly strengthening negative correlations. A similar plot with the Southern Oscillation index in place of Niño-3.4, although noisier, shows exactly the same monthly evolution in this long time frame (not shown). In spite of this, recent studies of ENSO–AIR correlations (Krishnamurthy and Goswami 2000; Mehta and Lau 1997; Krishna Kumar et al. 1999a,b) make use of ENSO indices contemporaneous with AIR to study their relationship through time. In this study we will use August–November Niño-3.4 as the pertinent ENSO index.

Interdecadal variability of the ENSO–AIR relationship (EAR) is evident when the correlation between their indices is viewed in a sliding window. Figure 1b shows these correlations in three sliding windows ranging in width from 11 to 21 yr. Although correlations in various windows do not always agree, the interdecadal swings in the relationship are common to all sliding window widths. The average between correlations in the three sliding windows is computed at each central year and smoothed with a running median nonlinear filter to robustly define interdecadal variability in EAR (thick line in Fig. 1a). Decades of strong and significant correlations, such as the 1890s and early 1900s, late 1930s to late 1940s, and mid-1960s to late 1970s, alternate with decades of apparently weak EAR. This low-frequency evolution of EAR is robust to the choice of ENSO index and sliding window width. A strong relationship persisting for over a decade exhibits typical correlation magnitudes of 0.7–0.8 (significant with 99% confidence level estimated for even the narrowest window of 11 yr), alternating with epochs of considerably weaker correlation.

b. Physical causes?

Interdecadal EAR modulation may be accomplished through low-frequency variability in the large-scale ocean–atmosphere system. However, detailed diagnostic analyses of SST and atmospheric pressure fields did not reveal any plausible physical causes. For example, no significant relationships between EAR and tropical or extratropical low-frequency climate modes could be detected.

c. Typical behavior

The low-frequency modulation described above is not unique to the ENSO–AIR relationship. Correlations between any pair of linearly related or unrelated climatic time series that vary on interannual timescales will exhibit low-frequency modulation. This is illustrated below in the context of the Asian summer monsoon and ENSO.

AIR may not be representative of the Asian summer monsoon: the Indian subcontinent represents only a region of the area affected by the Asian monsoon. Moreover, AIR is unduly influenced by daily extremes (Stephenson et al. 1999). Consequently, we have computed an alternative index of Asian monsoon rainfall. Principal components analysis (PCA) was applied to a southeast Asian rectangle (20°S–50°N, 50°–130°E) of the global gridded June–September rainfall data from the Climatic Research Unit, University of East Anglia, Norwich, United Kingdom (Hulme et al. 1998). The leading principal component (PC1) is defined as the monsoon rainfall index (MRI). It explains 15% of the summer-to-summer (June–September) rainfall variability during the period 1900–98 in southeast Asia, the spatial domain of the PCA. MRI is most representative of rainfall in eastern China, Indonesia/Malaysia, and India. The temporal evolution of correlations between monthly Niño-3.4 and MRI (not shown) closely corresponds to that between monthly Niño-3.4 and AIR (Fig. 1a).

Running correlation of the ENSO–MRI relationship (EMR) is displayed in Fig. 2b in an identical way to EAR (Fig. 2a). Although the mean correlation over the full record is similar ($r \approx -0.6$), EMR is characterized by much larger decadal variability than EAR, and the temporal evolution of EMR seems to occur on longer timescales. In any event, EAR and EMR themselves are uncorrelated ($r = 0$). Does this mean that a linear relationship between the two indices of Asian monsoon rainfall (AIR and MRI) is unstable on decadal timescales? The answer is clearly seen in Fig. 2c. In fact, any two year-to-year measures of the Asian monsoon will exhibit decadal swings in their running correlations. AIR, for example, is known to exhibit unstable rela-

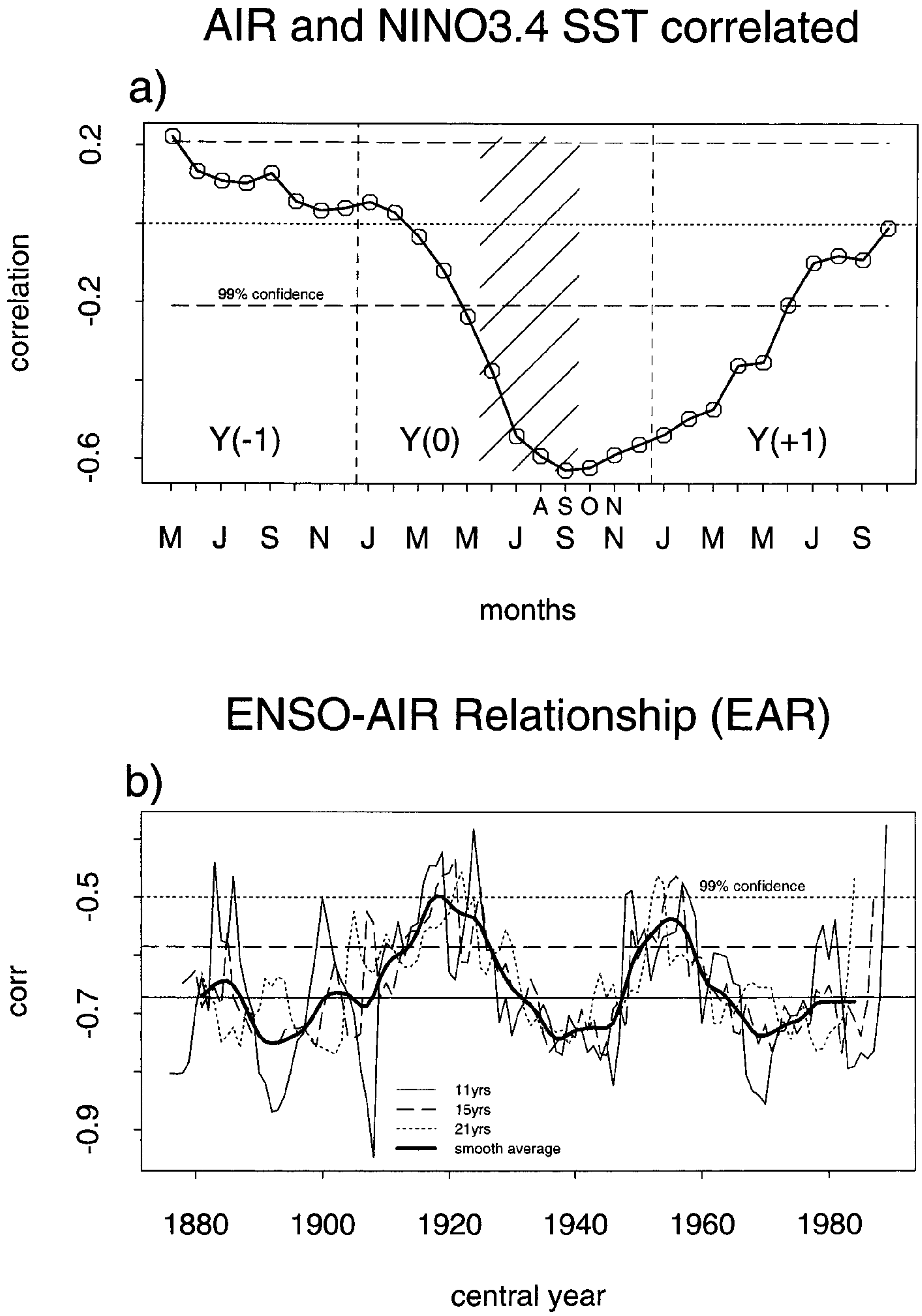

FIG. 1. (a) Correlation of monthly Niño-3.4 SST with AIR. The slanted lines represent Jun–Sep, the season when AIR is defined. Vertical dashed lines mark the beginning of a calendar year. Horizontal long dashed lines are 99% confidence intervals. (b) Correlation between Aug–Nov (ASON) average Niño-3.4 and AIR in sliding windows 11, 15, and 21 yr wide (thin solid, long, and short dashed lines, respectively). Horizontal lines represent respective 99% confidence intervals. The thick solid line is a smoothed average of the correlations in the three sliding windows. We take this line to represent the EAR.

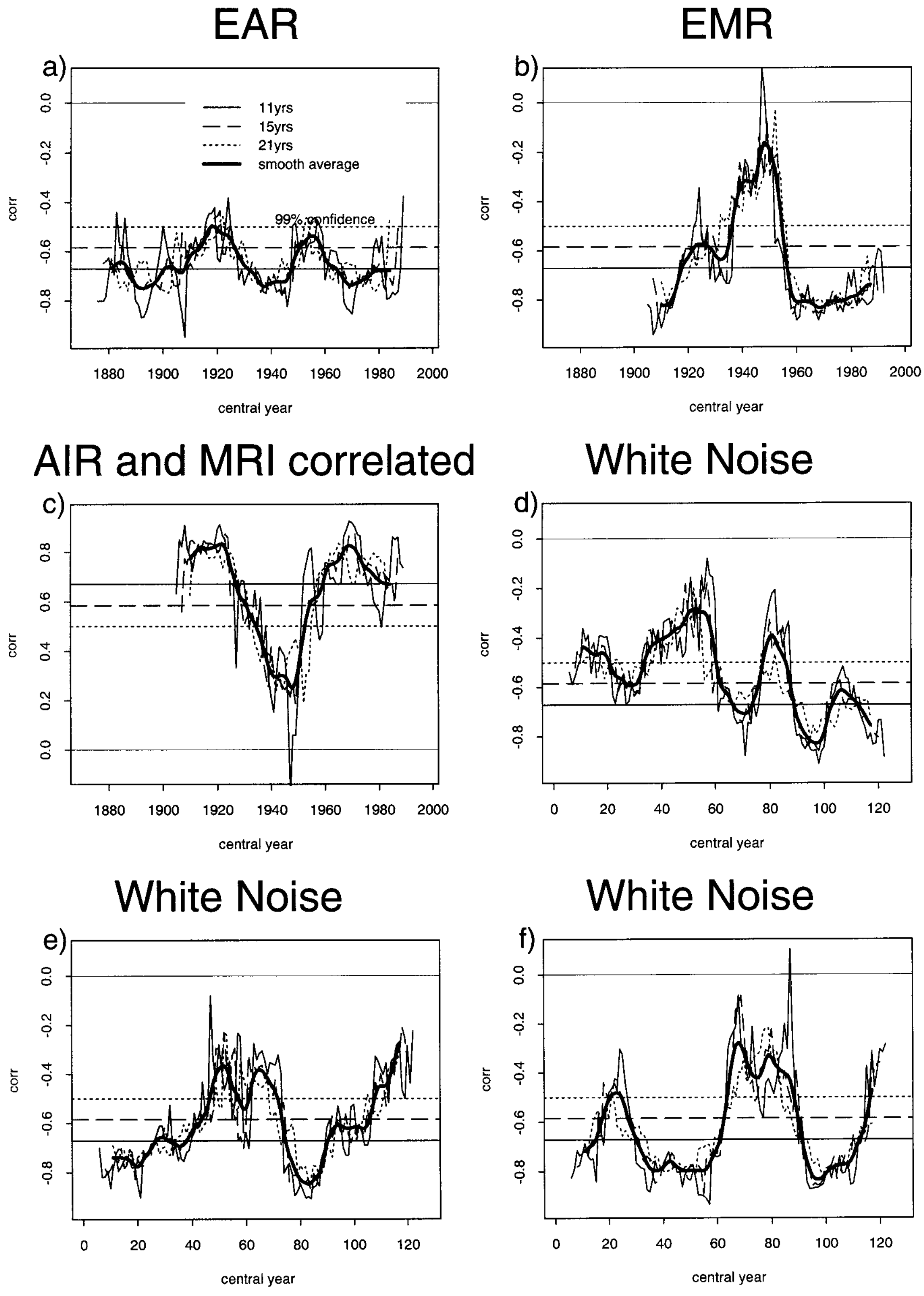

FIG. 2. (a) EAR (same as Fig. 1b) replotted on a common plotting region for easy comparison. The sliding correlation analyses for different pairs of time series displayed in (b)–(f) were performed in *exactly* the same manner. (b) ENSO–MRI sliding correlation analysis (EMR); (c) AIR–MRI sliding correlation analysis: the thick line is an internal monsoon coherence index; (d)–(f) correlation analyses for random pairs of white noise time series correlated at the same level as AIR and Niño-3.4 (see text).

tionships with regional Asian monsoon circulation indices (e.g., Parthasarathy et al. 1991). So, even the internal coherence of the Asian monsoon is decadally variable. Parenthetically, this phenomenon is reproduced by coupled ocean–atmosphere models (Gershunov et al. 1999).

d. Random processes

The presence of interdecadal modulation in relationships between interannual modes is ubiquitous while its physical causes remain elusive. Is it possible that no physical causes exist per se, but that the modulation is stochastically driven? We demonstrate that the simple interaction of two Gaussian noise processes is consistent with the result we have derived from the observations.

The ENSO and monsoon indices were tested for normality and independence. Normality was tested using both the one-sample Kolmogorov–Smirnov (KS) test and the chi-square goodness-of-fit test (χ^2). The p values for Niño-3.4 and AIR are 0.74 and 0.53 according to KS and χ^2, respectively. For AIR, the corresponding p values are 0.40 and 0.46—in all cases too large to reject the null hypothesis of normality at any reasonable confidence level. Akaike's information criterion was used to estimate the ''best'' autoregressive model, which turned out to be order zero for all indices. For example, order-one autoregressive coefficients estimated from the full 124-yr record of Niño-3.4 and AIR are 0.035 and -0.109, respectively, both statistically indistinguishable from zero. Therefore, these indices can be considered to be independent normal random variables.

Accordingly, we have simulated pairs of correlated white noise time series $x_1(t)$ and $x_2(t)$, where $x_1(t) = \varepsilon_1$ and $x_2(t) = cx_1(t) + \varepsilon_2$ with c being the overall correlation coefficient between the relevant time series estimated from the full record (-0.63 for EAR), $\varepsilon_1 \sim N(0, 1)$ and $\varepsilon_2 \sim N(0, 1 - c^2)$. The variance of ε_2 is $1 - c^2$ because x_1 explains c^2 of the variance of x_2. The total variance for both simulated time series is chosen to be 1 for simplicity since differences in mean and total variance have no effect on the results of running correlation analyses.

Figures 2d–f display running correlations between pairs of correlated white noise processes. Three simulated cases, analyzed and displayed in exactly the same manner as EAR, are adequate to give the flavor of possible outcomes. Based on these and 500 simulations in a bootstrapping scheme (Efron 1982), described below, we can make a major conclusion. The level of interdecadal variability in ENSO–AIR, ENSO–MRI, and AIR–MRI relationships, as well as relationships between many other pairs of climatic time series, is no larger than should be expected from pairs of Gaussian noise processes. Physically, this means the modulation can simply be considered as part of a stochastic process. In other words, even though many physical processes may be partially responsible for EAR modulation, it is not possible to distinguish their effects from stochastic noise in running correlation analyses.

From a sampling point of view, the low-frequency variability in sliding correlations between random time series should not come as a surprise. After all, small sample correlations between two variables from populations correlated at some level will always fluctuate around this level. Taking overlapping samples, as is done in sliding correlation analysis, will produce smoothly varying correlations. Statistically, this is an obvious result, but one not fully appreciated in climate research. Being aware of this behavior is important in order to be able to separate signal from noise in commonly used running correlation analyses. Without such awareness one may be tempted to look for physical explanations to stochastic noise. Therein lies the danger, for spurious relationships abound, especially when one deals with low-frequency phenomena diagnosed in short time series (Wunsch 1999). In general, the apparent presence of trends and periodicities in short filtered random time series is known as the ''Slutsky–Yule effect'' (Stephenson et al. 2000).

In the case of EAR, the decadal modulation is significantly *weaker* than might be expected by chance. Five hundred pairs of correlated white noise time series of the same length as AIR and Niño-3.4 (124 yr) were simulated for each correlation coefficient $c = \{0, 0.1, 0.2, \ldots, 0.9\}$. Then, running correlation analysis was applied to each pair of white noise time series for running window widths $w = \{5, 7, 9, \ldots, 31\}$ yr. Standard deviations of the time series of running correlations were then computed for each combination of running window width and population correlation coefficient (w, c). The 95th and 5th percentiles of the standard deviation are summarized in Table 1. The standard deviations of running correlations between observed time series must be outside these limits to be considered significantly (at the 95% confidence level in a one-tailed test) more or less variable than expected from noise, that is, sampling variability. The standard deviations (SDs) of running correlations between the observed time series for the 11-, 15-, and 21-yr windows, respectively, are as follows: SDs of EAR are 0.119, 0.085, and 0.078; SDs of EMR are 0.228, 0.212 and 0.205; and SDs of running correlations between AIR and MRI [i.e., monsoon coherence index (MCI)] are 0.228, 0.195, and 0.190. The reader is invited to verify using Table 1 ($w = \{11, 15, 21\}$, $c = 0.6$) that EAR is significantly *less* variable than expected from noise (SDs smaller than the 5th percentile in Table 1b), while EMR and MCI are characterized by standard deviations statistically indistinguishable from those expected from noise.

Of course, the above result holds if the bootstrapping and testing is done on the smoothed indices of EAR, EMR, and MCI. Table 1, however, provides a useful reference, a rule of thumb for testing the significance of swings in running correlations between time series of roughly similar length that can be considered inde-

TABLE 1. (a) 95th and (b) 5th percentiles of the bootstrapped standard deviation of running correlations as a function of running window width and correlation coefficient. See text for bootstrapping scheme. Shading is proportional to the bootstrapped percentile magnitudes (white = 0, black = 1).

a) 95th %-ile

correlation x 10 \ window width	5	7	9	11	13	15	17	19	21	23	25	27	29	31
9	0.25	0.18	0.14	0.11	0.1	0.09	0.08	0.08	0.07	0.07	0.07	0.06	0.06	0.05
8	0.36	0.27	0.22	0.19	0.17	0.16	0.14	0.13	0.12	0.12	0.11	0.1	0.1	0.09
7	0.42	0.33	0.28	0.25	0.22	0.2	0.19	0.18	0.17	0.16	0.15	0.14	0.14	0.13
6	0.46	0.37	0.32	0.29	0.26	0.24	0.22	0.21	0.2	0.19	0.18	0.17	0.16	0.16
5	0.5	0.41	0.36	0.32	0.29	0.27	0.25	0.24	0.23	0.22	0.21	0.2	0.2	0.19
4	0.52	0.43	0.38	0.34	0.31	0.29	0.28	0.26	0.25	0.24	0.23	0.22	0.21	0.2
3	0.53	0.44	0.39	0.36	0.33	0.31	0.29	0.27	0.26	0.25	0.24	0.23	0.22	0.21
2	0.55	0.46	0.41	0.38	0.34	0.32	0.31	0.29	0.28	0.27	0.25	0.25	0.24	0.23
1	0.55	0.47	0.42	0.39	0.36	0.33	0.32	0.3	0.29	0.27	0.26	0.25	0.24	0.23
0	0.55	0.46	0.41	0.38	0.35	0.33	0.31	0.3	0.29	0.27	0.27	0.26	0.25	0.24

b) 5th %-ile

correlation x 10 \ window width	5	7	9	11	13	15	17	19	21	23	25	27	29	31
9	0.09	0.06	0.05	0.04	0.03	0.03	0.03	0.02	0.02	0.02	0.02	0.02	0.02	0.01
8	0.17	0.12	0.09	0.08	0.07	0.06	0.05	0.05	0.04	0.04	0.04	0.04	0.03	0.03
7	0.22	0.16	0.13	0.1	0.09	0.08	0.07	0.07	0.06	0.06	0.05	0.05	0.04	0.04
6	0.29	0.21	0.17	0.14	0.12	0.11	0.1	0.09	0.08	0.07	0.07	0.06	0.06	0.05
5	0.33	0.24	0.19	0.17	0.15	0.13	0.11	0.1	0.09	0.08	0.08	0.07	0.07	0.06
4	0.36	0.27	0.22	0.19	0.16	0.14	0.13	0.12	0.11	0.09	0.09	0.08	0.07	0.07
3	0.39	0.29	0.24	0.21	0.18	0.16	0.14	0.13	0.12	0.11	0.1	0.09	0.08	0.08
2	0.42	0.32	0.26	0.22	0.19	0.17	0.15	0.14	0.12	0.11	0.11	0.1	0.09	0.08
1	0.42	0.33	0.26	0.22	0.19	0.17	0.15	0.13	0.12	0.11	0.1	0.09	0.08	0.08
0	0.43	0.33	0.27	0.23	0.2	0.18	0.16	0.14	0.13	0.12	0.11	0.11	0.1	0.09

pendent normal. Most observed unfiltered annually resolved climatic time series fit this description.

For the relationship between ENSO and Indian monsoon rainfall, this analysis suggests existence of a set of deterministic physics that partially stabilizes the ENSO–AIR interaction so that it is the *stability* of EAR that may require physical explanation, not the lack thereof. It is also possible that EAR experienced larger decadal swings before the instrumental record and may experience larger swings in the future. In general, because of the shortness of the instrumental record, these swings can appear deceptively deterministic, seem to be correlated with other low-pass-filtered modes of climate variability, or even look periodic, but in fact they do not necessarily reflect more than typical stochastic behavior of random processes.

3. Conclusions

Relationships between any pair of observed interannual climate modes are expected to fluctuate considerably at lower frequencies in much the manner expected of purely stochastic processes. While it is possible that some of this modulation is physically rooted and may be predictable, much of it may be stochastic and, hence, physically unpredictable. Before making claims one way or the other, however, we suggest using the bootstrap (Efron 1982) as an integral part of a running correlation analysis to test whether the low-frequency modulation of a relationship between any two time series is larger, smaller, more periodic, or in any other way significantly unlike that which would be expected from two random time series with the same statistical properties. In the example presented here, EAR tested to be more *stable* than would be expected from pairs of white noise time series, suggesting that processes *limiting* the level of stochastic variability in the ENSO–AIR interaction need to be explained. Without an explanation, we must assume that the instrumental record is not representative of the true level of EAR variability.

In any case, the expectation of large low-frequency fluctuations in the relationship between any two climate time series due specifically to random processes has grave implications for climate predictability on seasonal–interannual timescales. More generally, the existence of such stochastically driven low-frequency modulation suggests that much caution is needed in physically interpreting relationships between interannual and other ''high-frequency'' climate modes.

Acknowledgments. The National Science Foundation, Grant ATM 99-01110, supported this work. Constructive comments by three anonymous reviewers and Dr. Francis Zwiers, the editor, are appreciated. The lead author gratefully acknowledges discussions on statistical matters with Dr. Ania Panorska.

REFERENCES

Efron, B., 1982: *The Jackknife, the Bootstrap, and Other Resampling Plans.* Society for Industrial and Applied Mathematics, 92 pp.

Gershunov, A., N. Schneider, T. Barnett, and M. Latif, 1999: Decadal variability of the Asian monsoon. Preprints, *10th Symp. on Global Change Studies,* Dallas, TX, Amer. Meteor. Soc., 124–125.

Hulme, M., T. J. Osborne, and T. C. Johns, 1998: Precipitation sensitivity to global warming: Comparison of observations with HadCM2 simulations, *Geophys. Res. Lett.,* **25,** 3379–3382.

Krishna Kumar, K., M. K. Soman, and K. Rupa Kumar, 1995: Seasonal forecasting of Indian summer monsoon rainfall: A review. *Weather,* **50,** 449–466.

——, R. Kleeman, M. A. Cane, and B. Rajagopalan, 1999a: Epochal changes in Indian monsoon–ENSO precursors. *Geophys. Res. Lett.,* **26,** 75–78.

——, B. Rajagopolan, and M. A. Cane, 1999b: On the weakening relationship between the Indian Monsoon and ENSO. *Science,* **284,** 2156–2159.

Krishnamurthy, V., and B. N. Goswami, 2000: Indian monsoon–ENSO relationship on interdecadal timescale. *J. Climate,* **13,** 579–594.

Mehta, V. M., and K.-M. Lau, 1997: Influence of solar irradiance on the Indian monsoon–ENSO relationship at decadal-multidecadal time scales. *Geophys. Res. Lett.,* **24,** 159–162.

Normand, C., 1953: Monsoon seasonal forecasting. *Quart. J. Roy. Meteor. Soc.,* **79,** 463–473.

Pant, G. B., K. Rupa Kumar, B. Parthasarathy, and H. P. Borgaonkar, 1988: Long-term variability of the Indian summer monsoon and related parameters. *Adv. Atmos. Sci.,* **5,** 469–481.

Parthasarathy, B., K. R. Kumar, and A. A. Munot, 1991: Evidence of secular variations in Indian Monsoon rainfall–circulation relationships. *J. Climate,* **4,** 927–938.

Stephenson, D. B., K. Rupa Kumar, F. J. Doblas-Reyes, J.-F. Royer, F. Chauvin, and S. Pezzulli, 1999: Extreme daily rainfall events and their impact on ensemble forecasts of the Indian monsoon. *Mon. Wea. Rev.,* **127,** 1954–1966.

——, V. Pavan, and R. Bojariu, 2000: Is the North Atlantic oscillation a random walk? *Int. J. Climatol.,* **20,** 1–18.

Walker, G. T., 1924: Correlation in seasonal variations of weather. IV: A further study of world weather. *Mem. Indian Meteor. Dept.,* **24,** 275–332.

——, and E. W. Bliss, 1932: World weather. V. *Mem. Roy. Meteor. Soc.,* **4,** 53–84.

Wallace, J. M., E. M. Rasmusson, T. P. Mitchell, V. E. Kousky, E. S. Sarachik, and H. von Storch, 1998: On the structure and evolution of ENSO-related climate variability in the tropical Pacific: Lessons from TOGA. *J. Geophys. Res.,* **103,** 14 241–14 260.

Webster, P. J., V. O. Magaña, T. N. Palmer, J. Shukla, R. A. Tomas, M. Yanai, and T. Yasunari, 1998: Monsoons: Processes, predictability, and the prospects for prediction. *J. Geophys. Res.,* **103,** 14 451–14 510.

Wunsch, C., 1999: The interpretation of short climate records, with comments on the North Atlantic and Southern Oscillations. *Bull. Amer. Meteor. Soc.,* **80,** 245–255.

Yasunari, T., 1990: Impact of the Indian monsoon on the coupled atmosphere/ocean system in the tropical Pacific. *Meteor. Atmos. Phys.,* **44,** 29–41.