

## Potential for Long-Range Prediction of Monthly Mean Surface Temperatures over North America

DENNIS J. SHEA AND ROLAND A. MADDEN

*National Center for Atmospheric Research,\* Boulder, Colorado*

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### ABSTRACT

Using more than three times as many stations and time series of daily data that are generally 1.5–3.0 times longer than those in a previous study, estimates of the natural variability, also known as climate noise, of surface air temperatures are extended over most of North America. The potential for long-range prediction of monthly means is determined by comparing the actual interannual variability of monthly means with the climate noise that is assumed to be unpredictable at long range. The climate noise estimates are typically larger during winter than during the other seasons. Nonetheless, the potential for long-range prediction is, generally, greatest for January and least for April. During January, temperatures nearest the oceans are more predictable than those for the central portions of North America.

The low-frequency white-noise statistical model that is used to estimate the unpredictable climate noise is compared with time series of (near) surface temperatures from a general circulation model to confirm its credibility. The estimates of the potential for prediction are tested further to establish their sensitivities to a critical parameter of the statistical model and to spatial averaging.

### 1. Introduction

A certain amount of variability of time-averaged meteorological data is to be expected due to statistical sampling variations alone. That is, one monthly average of temperature at a given location will differ from another because each is a finite time average of daily values that results from a continuous process of passing weather systems. It represents variability that cannot be deterministically predicted at long range (about two weeks). This sampling variability of time-averaged weather that is strictly due to the atmosphere's internal dynamics is referred to as natural variability or "climate noise." Here, estimates of the climate noise for monthly averages over North America are made and compared with the actual interannual variability of monthly means. The observed interannual variability of monthly means is assumed to consist of a "climate signal" and the climate noise. The climate signal is presumed to arise from changing external conditions such as slowly varying sea surface temperatures, the greenhouse effect, etc. Generally, any process whose time scale is long relative to daily weather fluctuations is considered to be external. Where the interannual

variability of monthly means exceeds that suggested by climate noise it is concluded that the signal is large enough to potentially allow long-range prediction.

The conceptual framework for estimating the climate noise assumes that there will be no climate signal or climate change with constant external conditions. Lorenz (1968, 1976) has indicated that this may not be the case. The atmosphere may be "intransitive" or "almost intransitive." This possibility is probably not of particular concern when we estimate climate noise, but it may result in overestimating the potential for prediction since intransitivity could introduce additional variability that offers no possibility of prediction. However, if the atmosphere resides in distinct states for a relatively long time due to "almost intransitivity," then recognition of the current state could allow for skill in long-range prediction.

This work extends earlier papers on the subject (Madden 1976, 1981; Madden and Shea 1978, hereafter MS) by using 25 to 80 years of daily temperature data from approximately 350 United States and Canadian stations versus 22 to 24 years of daily data from 107 stations over the United States only, as done in MS. In addition, comparisons with (near) surface temperatures from a 6000-day, perpetual January simulation of a general circulation model (GCM) help to demonstrate the credibility of the "low-frequency white-noise" statistical model that forms the basis for estimating the climate noise.

The data used are described in section 2. The rationale behind approaching time-averaged temperature

\* The National Center for Atmospheric Research is sponsored by the National Science Foundation.

Corresponding author address: Dennis J. Shea, National Center for Atmospheric Research, P.O. Box 3000, Boulder, CO 80307-3000.

data as consisting of unpredictable climate noise and potentially predictable signals is briefly discussed in section 3. Section 4 contains the estimates of climate noise, and comparisons with the actual interannual variability of monthly means to provide a measure of the potential for long-range prediction at various locations for the months of January, April, July, and October. In section 5 there is a discussion of the sensitivity of results to the assumptions, and the conclusions are given in section 6.

**2. Data**

Daily mean temperatures (average of the minimum and maximum value for each 24-h period) from approximately 350 United States and Canadian stations were used. The geographical distribution of these stations and the number of years of data may be described as follows: generally, U.S. stations east of the Rockies, west of Pennsylvania, and north of 36° of latitude have 60–80 years of daily data. Most of the rest of the United States has 40–60 years of daily data with the exception of Texas where only 20–30 years of temperature data were available. Canadian stations south of 55°N generally had more than 40 years of daily data. The station density and the number of years with usable data drops considerably north of 55°N. More details concerning the data may be found in Shea (1984a). The majority of United States data were obtained from NCAR and the National Climate Data Center while the Canadian data were obtained from the Atmospheric Environment Service of Canada.

**3. Estimating climate noise**

Estimating the potential for long-range prediction is approached as an analysis of variance problem as described by Jones (1975, 1976). The variance within seasons, which is presumed to consist of only variability due to weather systems that are unpredictable at long range (climate noise), is compared to that between seasons, which is presumed to be made up of both the climate noise and any potentially predictable climate signals. To estimate the climate noise, spectra within seasons are computed using daily data; and from them an expected variance of monthly means is determined. That is

$$\sigma_N^2 = \int_{-\infty}^{\infty} S(f) |H_N(f)|^2 df \quad (1)$$

where  $\sigma_N^2$  is the variance of the climate noise of a time-average of length  $N$ . For monthly means  $N$  is 30 or 31.  $S(f)$  is the spectrum of daily data within seasons,  $f$  is the frequency ( $\text{day}^{-1}$ ), and  $H_N^2(f)$  is the power transfer function of the process of averaging  $N$  values.

The spectrum of daily data at each station,  $S(f)$ , was estimated by the following procedure: (i) the mean annual cycle was removed using a truncated Fourier series consisting of the first six harmonics with decreas-

ing weights of 0.833, 0.5, and 0.167 applied to the latter three harmonics; (ii) the entire record was divided into 96-day, slightly overlapping seasons beginning either 1 March, 1 June, 1 September, or 1 December for spring, summer, fall, or winter; (iii) each seasonal mean was subtracted from the daily values; (iv) the resulting daily anomaly values for each season were tapered and Fourier transformed; and (v) the coefficients were squared and averaged over all available years to yield a mean seasonal spectrum. Ideally, by subtracting individual seasonal means, the spectrum only reflects variability on time scales of two days ( $0.5 \text{ day}^{-1} = \text{Nyquist frequency}$ ) to 96 days. It is assumed that weather variations are uncorrelated at very long time scales and that the spectrum due to weather is constant or white at periods longer than 96 days. This low frequency white noise (LFWN) extension is similar to modeling the near zero frequency estimate of  $S(f)$  by a first order autoregressive process (Madden 1976, 1983). For more information on this point see Trenberth (1984a), who discusses in detail several methods of adjusting a sample variance in order to avoid underestimating the population variance. One method is the LFWN extension used in this study.

The actual variance of monthly means is computed in the standard way; that is,

$$\sigma_A^2 = \frac{1}{n-1} \sum_{i=1}^n (T_i - \bar{T})^2 \quad (2)$$

where  $n$  is the number of years,  $T_i$  is the mean temperature of the  $i$ th month, and  $\bar{T}$  is the grand mean temperature over all available years. The ratio  $\sigma_A^2 / \sigma_N^2$  gives a measure of the potential for long-range prediction of monthly mean temperatures. Where  $\sigma_A^2 > \sigma_N^2$  we assume that the excess variance is, at least, potentially predictable.

In principle, the separation of variability to that within seasons and that between seasons is straightforward. In practice, we really want to separate variance caused by internal dynamics (climate noise) as manifest by the daily weather, from that which may be caused by changing external conditions that might constitute predictable signals. Many of the problems involved have been underscored by Shukla (1983), Madden (1983), and Trenberth (1984b). An overview is provided by Zwiers (1987) who used an atmospheric GCM to study potential long-range prediction. An especially troublesome problem is that slowly changing external conditions probably have some influence on the daily data within a season. This could make the autocorrelation in the data larger than it would be under the influence of only weather variations. As a consequence the low frequency,  $1/96 \text{ day}^{-1}$ , spectral estimate and thus  $\sigma_N^2$  will be overestimated. Trenberth (1984b) used simulated data to study this problem. He added a reasonable quasi-biennial oscillation to climate noise modeled by a red-noise process, and found that

the methods used here only slightly overestimated the true climate noise. In section 5, the credibility of the LFWN statistical model is tested with the aid of a perpetual January simulation of the NCAR Community Climate Model. In addition, we present results of further sensitivity studies to assess something more of the magnitude of uncertainty in our estimates of climate noise.

#### 4. Results

Estimates of the standard deviation of the climate noise,  $\sigma_N$ , of monthly mean of surface air temperatures for winter, spring, summer, and fall based on Eq. (1) are shown in Fig. 1. Generally, minimum values of  $\sigma_N$  tend to be found along the coasts of the continent,  $\sigma_N$  estimates are less in the south than in the north, and

maxima are found in the interior and in winter. During winter and fall the largest  $\sigma_N$  values lie near the Rocky Mountains. As an example, we interpret these  $\sigma_N$  estimates to mean that 31-day monthly average temperatures during winter over parts of Montana and Alberta would have a standard deviation of  $>4^\circ\text{C}$  simply as a result of sampling variations due to daily weather variability.

The ratios  $\sigma_A^2/\sigma_N^2$  (Fig. 2) are similar in most respects to corresponding monthly values published in MS over the United States. Some differences are found over the southeastern United States where the previous ratios exceeded 2.0 for January and are less than 2.0 here in Fig. 2. Also, October values exceed 1.5 over most of the Great Plains of the United States in MS, while they are generally less than 1.5 here. The relative minimum in the ratio over the central United States

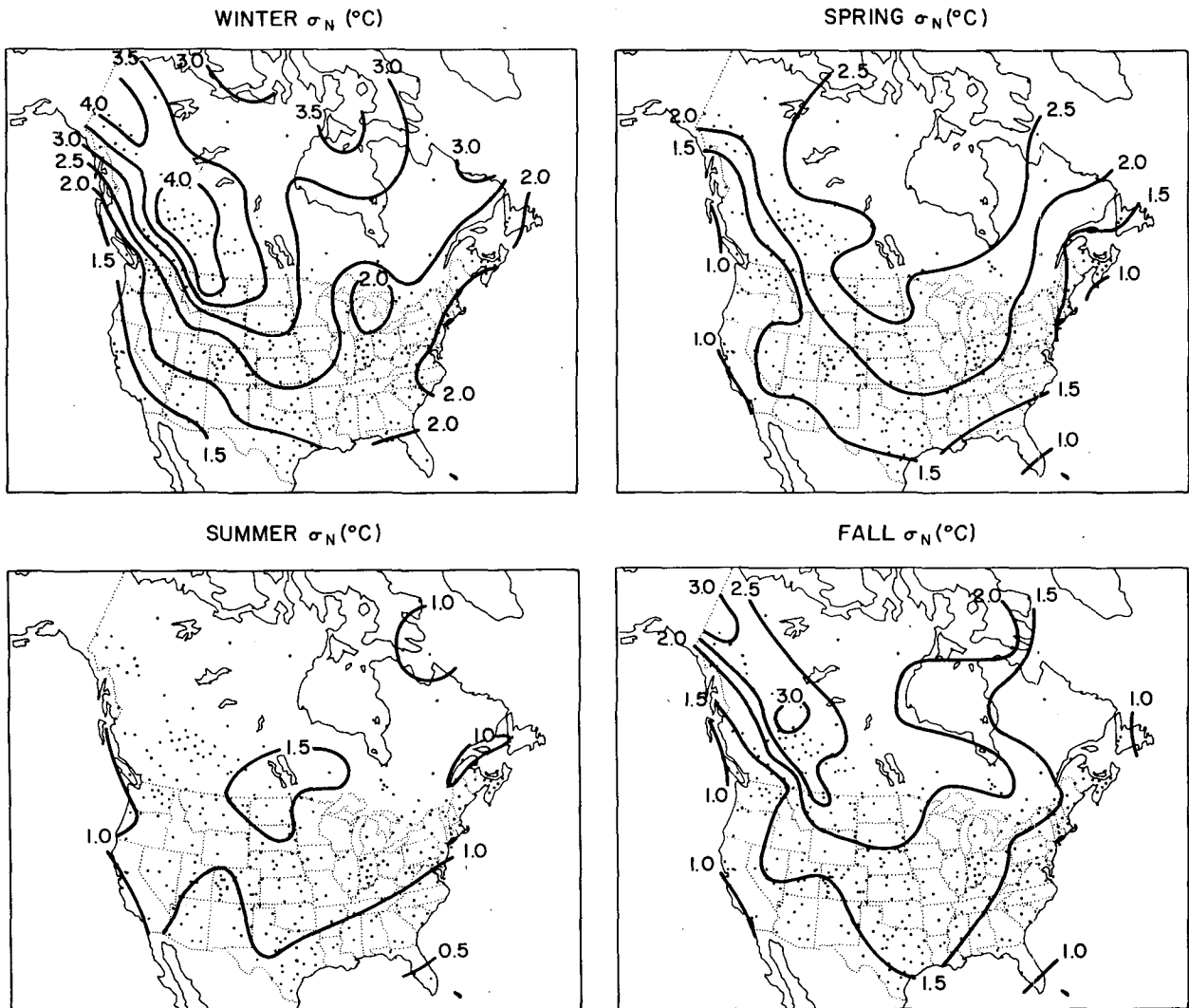


FIG. 1. Standard deviation in  $^\circ\text{C}$  of the estimated climate noise ( $\sigma_N$ ) for monthly mean temperatures during winter, spring, summer, and fall.  $N = 31$  for winter, summer, and fall; and  $N = 30$  for spring. Dots represent location of stations.

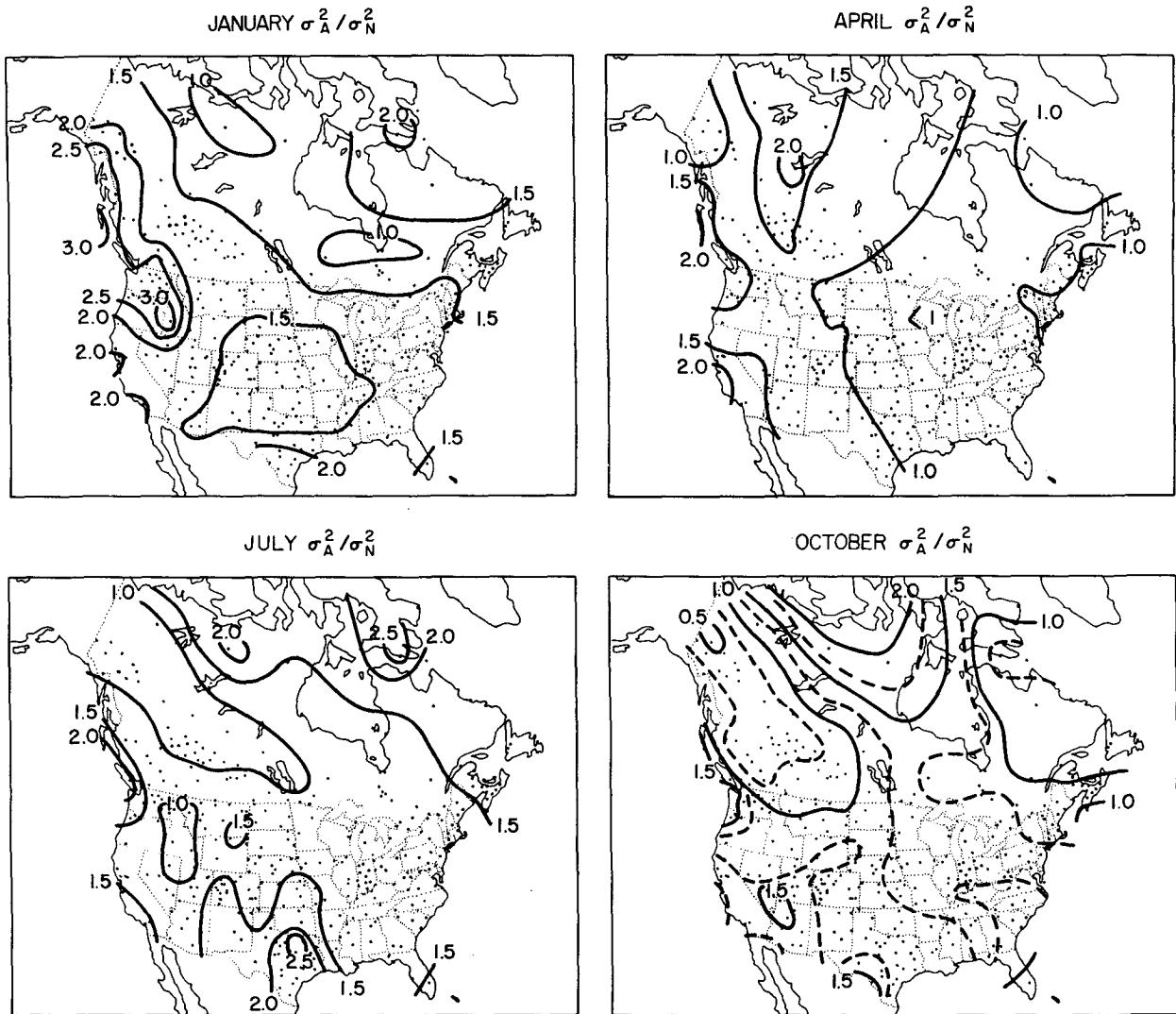


FIG. 2. Ratio of actual interannual variance of January, April, July, and October monthly mean temperatures to the variance of the climate noise of the appropriate season (winter, spring, summer, and fall; respectively).

during January is a feature that is common to other studies (MS; Madden 1981; Barnett 1981). Not surprisingly, the potential for long-range prediction tends to be largest near the coasts in proximity to the long-memory oceans although there are relative maxima over the interior of Canada during all seasons but winter. In particular, the ratios indicate that the potential for long-range prediction of surface air temperatures is greatest for January and least for April.

The patterns shown in Fig. 2 are quite similar to those of Van den Dool et al. (1986a; their Figs. 3–6), who studied the persistence of monthly air temperatures over the United States, and Van den Dool et al. (1986b), who studied summer persistence over Canada. The regions of largest ratios correspond to those of greatest persistence. Some of this persistence might reflect signals associated with a quasi-biennial oscillation,

the southern oscillation, or very low frequency trends as discussed in MS and Madden (1981).

The “signal-to-noise” ratios are  $F$ -ratios with variable numbers of degrees of freedom (df) in both the numerator and denominator. The df for the numerator are the number of years of, for example, January monthly means minus one. The df in the denominator are a function of the shape of the spectrum,  $S(f)$ , and were calculated using the method of Blackmon and Tukey (1958; p. 24). Thus, significance levels may be calculated. For example, areas over the Pacific Northwest during winter are significantly larger than one at the 5% level. However, primarily because of uncertainties in estimating parameters of the LFWN model with real data, we prefer to interpret the patterns of Fig. 2 in a relative sense. That is, the potential for long-range prediction is greater over the west coast of North

America than over the center of the continent in January, and greater in January than July over the Canadian Rockies, etc.

Doubt with respect to the *exact* size of the potential for long-range prediction notwithstanding, some quantitative interpretation is in order. A ratio of 1.5 means that 33% of the total variability exceeds climate noise and is therefore potentially predictable. For a ratio of 2.0, 50% of the total variability is potentially predictable. If we were to be able to predict 50% of the variance, we could predict shifts in temperature distributions from 50/50 (above/below average) to 25/75 more than 50% of the time (see Madden 1989). These would likely prove to be very useful predictions. On the other hand, over the central United States where ratios are, generally, relatively small the ability to accurately predict such large shifts in temperature would be rare. Exceptions are the high ratios over Texas and Oklahoma during July. Van den Dool (1988) shows a correlation pattern between monthly precipitation and temperatures during summer that is similar to the pattern of high ratios in this region for July. He speculates that soil moisture feedback could allow skillful long-range predictions there. Finally, it is interesting to note that the experience of the National Weather Service in predicting winter average temperatures is that regions of demonstrated skill and those of little or no skill parallel the  $\sigma_A^2/\sigma_N^2$  ratios for January temperatures (see maps of skill prepared by D. Gilman in Kalnay and Livezey 1985; Livezey 1990).

## 5. Discussion of the assumptions

Of the several assumptions used to determine the estimates of potential predicability, the most crucial is the LFWN extension at periods longer than 96 days. After multiplying the power transfer function  $H_N^2(f)$  with the spectrum,  $S(f)$ , the noise estimates are primarily determined by the spectral estimates at zero cycles/day (i.e., the LFWN estimate) and the lowest resolved estimate,  $1/96 \text{ day}^{-1}$  (see Table 1 in MS). In this section the results of a test of this assumption using a long GCM integration and the sensitivity of results using real data are discussed. The sensitivity of the calculated estimates (Fig. 2) to spatial averaging is also briefly described.

### a. Credibility of LFWN extension

Data generated by long simulations of GCMs with constant external conditions provide an opportunity to test the credibility of the LFWN model in principle. That is, they can provide insights into the low frequency behavior of idealized weather variations. Lau (1981) has shown that the spectra of the amplitudes of the first eigenvectors of 1000 and 500 mb height determined from 15 90-day winter simulations of a Geophysical Fluid Dynamics Laboratory, GCMs, increase monotonically from high frequency to the lowest re-

solved frequency,  $1/90 \text{ day}^{-1}$  (his Fig. 21). The GFDL model contains seasonal forcing but no other low frequency forcing other than possible changing snow cover and soil moisture. Bates and Blackmon (personal communication, 1982) have computed spectra based on the Community Climate Model at NCAR and find, in general, an increase in power from the highest to the lowest resolvable frequency,  $1/90 \text{ day}^{-1}$ . Straus and Halem (1981) studied the GLAS GCM sea level pressure data generated for fixed January conditions. Straus provided spectra at two grid points that were computed for, but not published with, their paper (personal communication, 1982). They have relative maxima near  $1/6 \text{ day}^{-1}$  but then increase to an absolute maxima at their lowest resolvable frequency  $1/30 \text{ day}^{-1}$ . These studies indicate that it is reasonable to assume that there is considerable low frequency variance in weather variations (i.e., the spectrum is red).

Data from a 6000-day perpetual January simulation from the NCAR Community Climate Model (Williamson 1983; called "CCM0B") were examined to specifically test the LFWN assumption. This simulation that was run with fixed sea surface temperatures was used by Branstator (1990) to examine low frequency atmospheric variability. The model grid is Gaussian with a resolution of about  $4.4^\circ$  of latitude and  $7.5^\circ$  of longitude giving 1920 grid points. At each grid point the 6000-day time series of temperatures nearest to but not at the surface (nominal 991-mb level) was broken into a variable number of 32, 48, 72, 96, 128, and 192 day "seasons" or segments after the 6000-day model linear trend was removed to minimize model bias. This allows for comparison of estimates of climate noise determined from the LFWN assumption beginning at  $1/32 \text{ day}^{-1}$  with those determined from its beginning at  $1/48 \text{ day}^{-1}$ , etc. If segment lengths of 32 days were to give estimates of the actual low frequency variance of the model data similar to those of 96 days, then it might be argued that the former could be used with real data, and the problem of the effect of slowly changing external on estimating climate noise would be minimized. On the other hand, we don't want segments so short that we seriously underestimate the low frequency variance associated with weather variations.

Fifty seasons for the segments of length 32, 48, 72 and 96 days were used, while for the 128 and 192 day segments 40 and 27 seasons were used; respectively. In the case of the 96-day segments, for example, time series were divided into 50 seasons at each of the 1920 grid points. Each 96-day segment was separated by 24 days to assure independence. Separations for other segment lengths differed from this yet they always exceeded three weeks. The spectra,  $S(f)$ , were computed as described in section 3. The LFWN extension was used to extend them to zero frequency and the noise estimates were calculated. The middle 31 days of each segment were used to compute the "monthly" means;

and  $\sigma_A^2$ , the variance about the overall monthly mean, was computed using Eq. (2). Since the ratio  $\sigma_A^2/\sigma_N^2$  is an  $F$ -ratio, the distribution of ratios from all grid points should approximate that of the  $F$ -distribution if  $\sigma_A^2 = \sigma_N^2$ . The distribution of ratios from the 1920 grid points of climate model data, the theoretical  $F$ -ratios, and their 5% and 95% limits for each of the segment lengths are presented in Fig. 3. Because the model results are systematically displaced to the right of the theoretical values for season lengths of less than

96 days, the tendency is for  $\sigma_A^2/\sigma_N^2 > 1$ . On the other hand, the use of season lengths of 96, 128, and 192 days yields ratios that agree reasonably well with the theoretical  $F$ -distribution. Therefore we conclude that, for these longer season lengths,  $\sigma_N^2$  is a good approximation for  $\sigma_A^2$ . Given sampling variations, these results indicate that the LFWN model is a good assumption when season lengths are about 96 days or so.

Since a LFWN statistical model that is based on segments as short as 96 days can adequately predict the

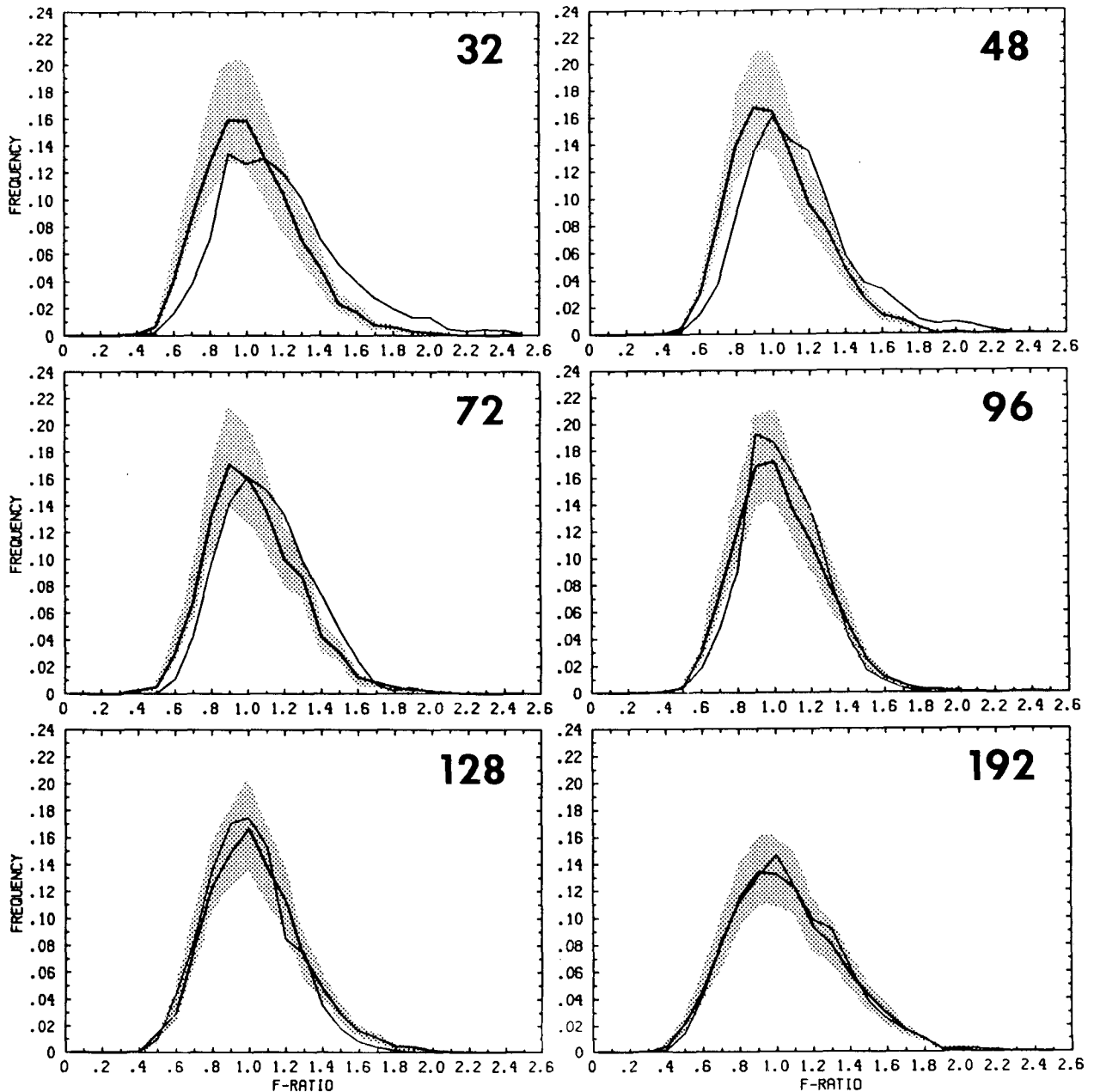


FIG. 3. Model (light) and theoretical (dark)  $F$ -distributions for 32, 48, 72, 96, 128, and 192 day season lengths. The stippled area indicates the 5% and 95% confidence limits about the theoretical curve.

variance of time averages in the absence of a changing external conditions, it is concluded that there is no evidence of “intransitivity” or “almost-intransitivity” over the 6000 model days in (near) surface temperatures in CCM0B. This conclusion seems to be at odds with those of Zwiers (1987) and Branstator (personal communication). They find considerable low-frequency variance that exceeds levels suggested by the LFWN model beginning at 96 days for 500 mb geopotential heights and surface pressures in simulations by the Canadian climate model and the NCAR CCM (the same data source as that used here). To investigate this we applied the same methodology (using 96-day seasons) to the CCM generated surface pressures and 500 mb geopotential heights and temperatures. The results (Fig. 4) show that the  $F$ -distributions associated with surface pressures and 500 mb geopotential heights are shifted to the right of the theoretical  $F$ -distributions confirming that there is low frequency variance in both mass field quantities. The  $F$ -ratio distribution for the 500 mb temperatures, however, indicates little or no low frequency variability over and above the LFWN estimates for 96-day seasons. This is consistent with the  $F$ -distribution for the (near) surface temperatures. A possible explanation for this is that the CCM contains some low frequency barotropic variability. In any event, the results indicate that the use of 96-day seasons does not overestimate the noise.

#### b. Sensitivity of results to the LFWN assumptions

An important test is to determine the sensitivity of the spectral estimates to the length of the season using real data. The CCM comparison suggests a seasonal segment should be 96 days or so long to avoid underestimating the climate noise. However, in practice, long seasonal segments increase the possibility that the resulting spectra will be affected by changing external conditions. To assess the effect of shorter seasons with real data, the calculations were repeated for 48- and 32-day seasons during winter only. The ratios using 48-day segments are very similar to those shown in Fig. 2. The only exceptions are the West Coast and the southeast United States, where the ratios increased slightly. It is an indication that the spectra at these stations are still “red,” while for the majority of stations the spectra have essentially become “white” by 48 days. The ratios for the 32-day segments are increased everywhere. The increase in ratios is geographically dependent with some extreme increases of 35%–50% west of the Rockies while in the center of the United States and Canada the ratios increased only 1% to 10%. Of course this is consistent with the model comparisons of Fig. 3; using 32- and 48-day seasons underestimates the noise more often than 96-day seasons. In neither case do the basic patterns change. That is, the potential for long-range prediction over the central portions of North America is, generally, considerably less than that over coastal regions.

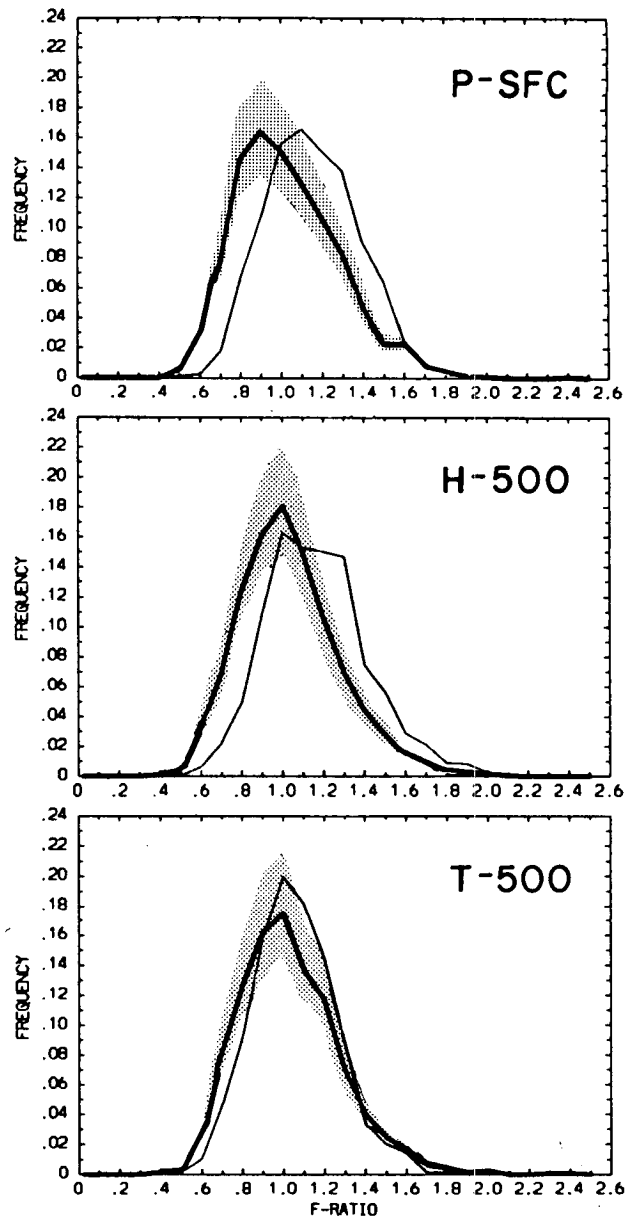


FIG. 4. Model (light) and theoretical (dark)  $F$ -distributions using 96 day season lengths for CCM surface pressures (top), 500-mb geopotential heights (middle), and 500-mb temperatures (bottom). The stippled areas indicates the 5% and 95% confidence limits about the theoretical curves.

#### c. Sensitivity to spatial averaging

Stations were grouped into 25 regions loosely guided by climatology and the desire to get a reasonable number of stations into each region [see Fig. 6 in Shea (1984b)]. The temperature data from each station within a region for each calendar day were averaged to form a single time series for each region. Then  $\sigma_A^2$  and  $\sigma_N^2$  were estimated for each region according to the methods described in section 3. It was hoped that

spatial averaging would minimize the estimates of  $\sigma_N^2$ , thus maximizing the relative size of the signal contained in  $\sigma_A^2$ . The character of the pattern is very similar to that shown in Fig. 2. Thus it is tentatively concluded that spatial averaging does not improve the estimates for potential long-range prediction.

## 6. Conclusions

The work by MS has been extended to include Canada. The updated estimates of climate noise and the potential for long-range prediction have been determined using more stations with longer time series and are generally consistent with those published earlier. For example, there is a relative minimum in the potential for long-range prediction over the central United States during January. Overall, the potential for long-range prediction is greatest in January and least in April.

The crucial LFWN assumption beyond 96-day periods has been shown to be a good statistical model by using a 6000-day simulation of the NCAR CCM in perpetual January mode. In practice, the noise estimates are sensitive to the length of the season used to calculate the seasonal spectra, however, the patterns of the potential for long-range prediction were not. Overall it seems that a seasonal length of 96 days for observed data is a prudent choice. Spatial averaging of the data did not, in general, improve the estimates for potential long-range prediction.

While there are admitted difficulties in estimating climate noise, we argue that values shown in Fig. 1 are reasonable, first order estimates, and any long-range predictions of temperature shifts that we are able to make will have to be large relative to Fig. 1 if they are to be of practical value.

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