9.5 A NEW WEATHER GENERATOR BASED ON SPECTRAL PROPERTIES OF SURFACE AIR TEMPERATURES

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1. INTRODUCTION

Weather generators are statistical models aimed at providing data to augment the existing climate record at a site or, through interpolation of model parameters, provide climate information where measured data are not available (Johnson et al. 1996; Wilks and Wilby 1999). Such models have several inter-connected components and usually simulate maximum and minimum daily surface air temperatures (T_{max} and T_{min}), solar radiation (R), and precipitation occurrence (P_o) and amount (P_a).

The most widely used weather generator is the autoregressive model introduced by Richardson (1981) and Richardson and Wright (1984), which is based on the multivariate autoregressive process described by Matalas (1967). Many studies have altered the original approach through changes in the way the parameters are computed (e.g., Schoof and Robeson, 2003), inclusion of additional variables (e.g., WXGEN, Nicks et al. 1990; GEM, Hanson and Johnson 1998), or relaxation of normality constraints for the added variables (e.g., Parlange and Katz 2000), but the basic structure of the model has remained unchanged. As shown in Schoof and Robeson (2003), even with improvements to the model parameterizations, autoregressive weather generators still occasionally produce fundamental simulation errors, such as negative diurnal temperature range (DTR) (e.g., T_{min} greater than T_{max}). Additionally, Harmel et al. (2002) have indicated that monthly T_{max} and T_{min} probability distributions are generally skewed, and that generating temperatures with the normal distribution can lead to physically unlikely values. In this study, we present an alternative to autoregressive weather generators based on spectral methods. It is anticipated that by removing normality constraints and focusing on T_{min} and DTR rather than T_{min} and T_{max}, some of these problems may be overcome.

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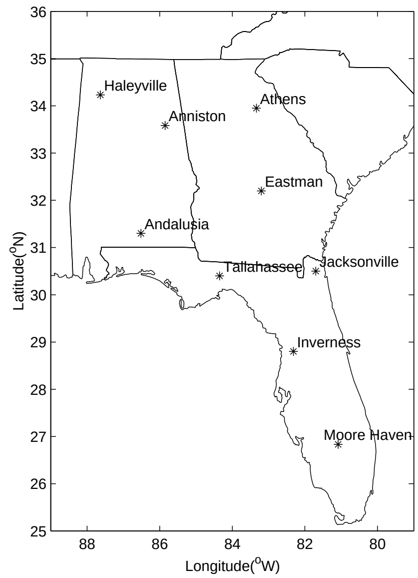

Figure 1: Map showing cooperative station locations.

2. STUDY AREA AND DATA

The weather generator described in this extended abstract is motivated by the research team's involvement with the Southeast Climate Consortium, a group consisting of members from six universities in the Southeast USA focused on climate variability and risks to agriculture, forestry, and water resources in the region (see http://secc.coaps.fsu.edu). Climate variability within the study region (Figure 1) exhibits strong links to El Niño/Southern Oscillation (ENSO), which, in turn, impacts the aforementioned sectors (Hansen et al. 1998, 1999). Our weather generator is therefore also conditioned on ENSO phase based on the Japanese Meteorological Agency tropical Pacific Ocean (4°S-4°N and 150°W-90°W) SST anomalies (JMA-SST; see Hanley et al. 2003), and the Florida Climate Center provides years with their respective ENSO phases (Table 1). In the remainder of this paper, we refer to La Niña as the cold phase and El Niño as the warm phase.

NWS cooperative station network data (T_{max}, T_{min} and precipitation) are used for parameterization and evaluation of the weather generator. We generate data for nine locations, each with data for at least 1950-2003 and less than 5% missing data for each ENSO phase (Table 2, Figure 1). Solar radiation data are not available for these stations. Therefore, our current focus is on generation of the temperature and precipitation variables. Methods for generation of radiation from the generated variables are currently being investigated.

Table 1: List of La Niña (cold SST), Neutral, and El Niño (warm SST) years as defined by the JMA-SST anomalies. ENSO years begin on October 1 of the posted year and end on September 30 on the subsequent year. For example, the 1997 El Niño year began on October 1, 1997 and ended on September 30, 1998.

La Niña Phase	Neutral Phase	El Niño Phase
1949, 1954, 1955, 1956 1964, 1967, 1970, 1971 1973, 1974, 1975, 1988 1998, 1999	1950, 1952, 1953, 1958, 1959, 1960, 1961, 1962, 1966, 1968, 1977, 1978, 1979, 1980, 1981, 1983, 1984, 1985, 1989, 1990, 1992, 1993, 1994, 1995, 1996, 2000, 2001	1951, 1957, 1963, 1965, 1969, 1972, 1976, 1982, 1986, 1987, 1991, 1997 2002

Table 2: List of NWS cooperative weather stations used in this study.

Station Name	State	COOP #
Andalusia	AL	10252
Anniston	AL	10272
Haleyville	AL	13620
Inverness	FL	84289
Jacksonville Intl AP	FL	84358
Moore Haven	FL	85895
Tallahassee	FL	88758
Athens	GA	90435
Eastman	GA	92966

3. WEATHER GENERATOR DESCRIPTION

3.1. Precipitation Occurrence

Our weather generator adopts the spell length approach to generate precipitation occurrence (Buishand 1978; Racsko et al. 1991). In this approach, alternating wet and dry spells are produced with random lengths based on probabilities computed on a monthly basis from the observed data. The lengths of the wet and dry spells are modeled using geometric distributions which reduces this approach to that of a two-state first-order Markov chain model, which has been demonstrated to work well in the southeastern USA (Wilks, 1999).

3.2. Precipitation Amount

Once the precipitation occurrence component of the weather generator generates a wet day, the precipitation amount is drawn from a mixed-exponential distribution:

$$f(x) = \frac{\alpha}{\mu_1}\exp\left(\frac{-x}{\mu_1}\right) + \frac{1-\alpha}{\mu_2}\exp\left(\frac{-x}{\mu_2}\right) \qquad (1)$$

where μ_1 and μ_2 are the means of two exponential distributions and α is the mixing parameter. Parameters for this distribution are determined through maximum likelihood estimation using the observed data and are computed separately for each month.

3.3. Minimum Temperature (T_{min}) and Diurnal Temperature Range (DTR)

The process of generating T_{min} and DTR begins by computing their monthly means and standard deviations for each month in the observed record and ENSO phase, as well as the wet and dry day means and standard deviations, and monthly skewness. The data for each individual month, T_t, are then detrended and subjected to a discrete Fourier transform and the resulting spectral estimates, $T_f T_f^*$, represent the temperature (either T_{min} or DTR) variance present in the data across different frequencies. By averaging the resulting $T_f T_f^*$ for each calendar month and ENSO phase, we find $H_f H_f^*$, an ensemble mean spectral estimate (e.g., the average T_{min} spectrum for January during the cold phase of ENSO). The square roots of the average spectral estimates, $\left|H_f\right| = \sqrt{H_f H_f^*}$ represents the amplitude of the variability across frequencies within each calendar month.

To generate data for a particular month and ENSO phase, we generate a white noise series with length equal to the number of days in the month, x_t. The spectrum of this white noise series, $X_f X_f^*$ is theoretically constant. Y_f is then produced by convolving the ensemble amplitude spectrum and the Fourier transform of the white noise series:

$$Y_f = \left|H_f\right| X_f \tag{2}$$

The inverse Fourier transform of Y_f, Y_t, is a new time series with the same length as the month in question containing deviations (from average) of T_{min} or DTR. The generated series is checked for proper skewness and absence of negative DTR before data generation continues. The model currently requires that the generated DTR is positive and than the skewness of both T_{min} and DTR is within 0.1 of the mean observed skewness for the month in question. If the generated sequence does not meet both of these requirements, a new white noise series is produced and the process is repeated. The wet day and dry day mean values are then drawn from a normal distribution with mean and standard deviation determined from the observed data. Once a day is determined to be wet or dry according to the methodology described in Section 3.1., the appropriate wet or dry day mean minimum temperature or DTR is added to each value comprising Y_t. We also compute the average trend for each calendar month and add it to the daily sequence to avoid discontinuities at the monthly boundaries.

4. WEATHER GENERATOR EVALUATION

We compare sequences generated by the spectral model with observed data to evaluate model performance. We also compare our generated temperature data with that produced by a WGEN-type autoregressive (AR) model to place the differences in the context of weather generators. The AR model used in this study is described by:

$$\begin{bmatrix} T_{\max} \\ T_{\min} \end{bmatrix}_i = A \begin{bmatrix} T_{\max} \\ T_{\min} \end{bmatrix}_{i-1} + B\varepsilon_i \tag{3}$$

where the left hand side of the equation represents the current day's values, the vector with subscript i-1 refers to the previous day's values, ε_i is a 2×1 vector of random N(0,1) variates, and A and B are 2×2 matrices determined from the observed lag-0 and lag-1 cross-correlation matrices. The residuals produced by Equation 4 are then multiplied by the daily standard deviation and added to the daily mean. The daily means and standard deviations used for this purpose are derived by fitting three harmonics to the daily means and standard deviations for each day of the year (see Figure 3). For this application, we use monthly station-specific parameterization for A and B as suggested by Schoof and Robeson (2003) and for consistency, the AR model uses the same precipitation occurrence and amount components as used with the spectral generator and separate parameter sets are determined for each ENSO phase. Parameter sets for both weather generators are derived from the same observed data. For each weather generator, a 100-year series is generated for each ENSO phase and evaluated relative to the 54-year historical record.

4.1. Precipitation occurrence

The spectral weather generator successfully reproduces the mean number of wet days on annual (within 4 days) and monthly (within 2 days) timescales. Application of a t-test to the differences indicates that they are not statistically significant (at α=0.05) for any of the stations tested during any of the three ENSO phases. On a monthly basis, the mean number of generated wet days is significantly different from observed (at α=0.05) only at Inverness, FL, during April of the warm ENSO phase and Jacksonville, FL during May of the cold ENSO phase.

Stochastic precipitation models typically underestimate interannual variability in precipitation although it is unclear whether this result arises from inadequate statistical representation of the precipitation process or failure to capture interannual variability in the physical processes governing precipitation occurrence (Wilks 1999). This variance underestimation problem is known as overdispersion and is defined as:

$$\left[\frac{\text{observed variance}}{\text{modeled variance}} - 1\right] \times 100\% \tag{4}$$

The interannual variability within the model presented here is dependent only on two properties: the variance of the number of wet days and the variance of wet-day precipitation amounts (Gregory et al. 1993; Katz and Parlange 1998; Wilks 1999). The weather generator presented here suffers from minor overdispersion in the number of wet days (Figure 2a). The interannual variance of the number of wet days, however, is not always underestimated and underdispersion (overestimation of variance) occurs for some months and ENSO phases (Figure 2a). Averaged over all stations and months, the overdispersion for the monthly number of wet days is 3.3%, 5.7%, and -1.1% for the cold, neutral, and warm ENSO phases, respectively. The interannual variability in the number of wet days is significantly different from observed only at Inverness, FL during the neutral ENSO phase, although differences in the standard deviation of the number of annual wet days exist across stations and ENSO phases. Generated and observed monthly interannual variances of the number of wet days are only significant (according to an F-test with α=0.05) at Inverness, FL during August of the neutral ENSO phase.

These results suggest that the weather generator adequately reproduces the mean number of annual and monthly wet days but slightly underestimates the interannual variability in the mean number of wet days during the cold and neutral ENSO phases and slightly overestimates the interannual variability during the warm ENSO phase. Hence, we conclude that the observed precipitation occurrence structure is well-represented, but that weather generators may benefit from inclusion of additional parameters which influence low frequency variability, even within a particular ENSO phase.

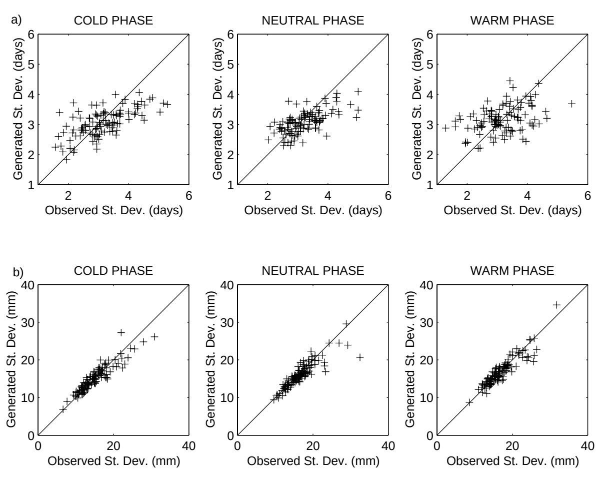

Figure 2: Monthly variance overdispersion for a) number of wet days, and b) wet-day precipitation amount. Points below the 1:1 line indicate underestimated variance (overdispersion), while those above the 1:1 indicate variance overestimation.

4.2. Precipitation Amount

On the daily timescale, the generated precipitation amounts exhibit strong agreement with observations. Mean wet-day precipitation amounts computed over the entire year are within 0.5 mm of observed values at all stations tested and for all three ENSO phases. When computed for each month, differences between generated and observed wet-day precipitation amounts are slightly larger, but less than 3 mm for all stations, months, and ENSO phases. Although these differences are large relative to those computed over the entire year, they are not statistically significant (based on a t-test with α=0.05) for any of the stations during any month or ENSO phase.

In general, the mean wet-day amounts exhibit better agreement with observations than the variances of wet-day amounts. The variance of wet-day precipitation amount computed using the entire year is significantly different from that observed (based on F-test with α=0.05) at two stations (Andalusia, AL during the neutral ENSO phase and Tallahassee during the cold and neutral ENSO phases). Variances of monthly wet-day precipitation amounts are significantly different from those observed at Andalusia, AL (March and October of neutral ENSO years), Jacksonville, FL (October of neutral ENSO years), and Tallahassee (June and September of neutral ENSO years). In each of these cases, the generated variance is less than the observed variance although variance overestimation (underdispersion) also occurs for some stations and months during each ENSO phase (Figure 2b). As noted in Section 4.1, the interannual variability is dependent on the variability in the number of wet days and the variance of wet-day precipitation amounts. As shown in Figure 2b, the variance of wet-day precipitation amounts exhibits greater agreement with observations than does the variance of the number of wet days. Averaged over all months and stations, the variance overdispersion for wet-day precipitation amounts is 0.7%, 3.7%, and 0.6% for the cold, neutral, and warm ENSO phases respectively.

The annual and monthly total precipitation amounts depend on both the wet-day amounts and the number of wet days. Differences in the generated and observed mean annual precipitation amount range (across stations) from -33.7 to 67.6 mm, -20.5 to 42.9 mm, and -40.1 to 38.8 mm for the cold, neutral and warm ENSO phases, respectively and are not significantly different at any station during any ENSO phase (based on a t-test with α=0.05). At the monthly timescale, agreement between observed and generated precipitation totals is slightly weaker, and the null hypothesis of equal monthly means is rejected (at α=0.05) for both September of the cold ENSO phase and April of the warm ENSO phase at Inverness, FL, due to both simulation of too many wet days and excessive precipitation amounts on those days.

4.3. Minimum Temperature (T_{min})

The annual mean daily minimum temperatures (T_{min}) produced by both the spectral weather generator and the AR weather generator exhibit excellent agreement with observations. Absolute differences between generated and observed annual mean daily T_{min} range from 0.0 to 0.2°C for both the spectral and AR models and are not significantly different from zero at any of the stations tested during each ENSO phase. When computed on a monthly basis, these absolute differences are larger, and range from 0.2 to 0.8°C and 0.4-1.5°C for the spectral and AR models, respectively. The differences reported above for the spectral model are not statistically significant (based on a t-test with α=0.05) for any station, month, or ENSO phase. Those for the AR model are not statistically significant during the cold and neutral ENSO phases with one exception (Inverness, FL during July of the cold ENSO phase). However, multiple stations exhibit statistically significant differences in monthly mean values of daily T_{min} for several months during the warm ENSO phase. Further inspection of the observed and generated data (Figure 3) shows that the 3-harmonic fit fails to capture a spring spike in daily T_{min} resulting in significant differences in March mean daily T_{min} at five stations (Andalusia, Inverness, Jacksonville, Moore Haven, and Eastman). Significant differences also occur during June (2 stations), July (2 stations), August (4 stations), and September (3 stations) due to a flattened seasonal cycle during these months during the warm ENSO phase (Figure 3). No significant differences occur at the three northernmost stations (Haleyville, Anniston, and Athens).

Both weather generators correctly reproduce the standard deviation of daily minimum temperatures at the annual timescale within 0.2°C. The spectral weather generator also correctly replicates the standard deviation of daily T_{min} for each month. The AR model has fewer statistically significant differences for the monthly standard deviation of mean T_{min} than monthly mean T_{min}, although the former are still significant for three stations (Anniston during neutral ENSO June, Inverness during cold phase June, neutral phase September, and warm phase June and September, and Moore Haven during neutral phase November and warm phase June, August, and September). These differences do not appear to be due to poor characterization of the seasonal cycle by the harmonics used in the AR model formulation.

In addition to the daily T_{min} statistics presented above, we also consider statistics describing the distribution of the monthly mean T_{min}. The spectral weather generator correctly reproduces the mean of the monthly mean T_{min} for each calendar month. Absolute differences in the monthly means are less than 1.2°C and insignificant in a statistical sense (based on a t-test with α=0.05). As with the mean daily T_{min}, mean monthly mean T_{min} values produced by the AR model are significantly different from those observed (based on a t-test with α=0.05) for multiple stations. As with the monthly means of the daily T_{min}, absolute differences are as large as 1.5°C and the largest differences occur at southern stations during the warm ENSO phase.

The interannual variance of T_{min} was examined in terms of both the variance of the annual means and the variance of the means for each calendar month. The former indicate that the year-to-year variations in annual mean T_{min} are substantially smaller in the generated data than in the observations. However, the interannual variability is quite small, so that in many cases statistical significance of the difference in observed and generated interannual variability is easily achieved. At the monthly timescale, the interannual variability is considerably larger, and although the generated interannual variability is smaller than observed for most stations and ENSO phases, the differences are not statistically significant for any of the locations tested during any of the three ENSO phases (based on an F-test with α=0.05). Similar levels of interannual variability are produced by the AR model, although differences in interannual variability of monthly mean T_{min} are found to be statistically significant at Inverness, FL during July and August of neutral ENSO years due to variance underestimation.

Of particular importance for agricultural applications are temperature extremes, and freeze events, in particular. Therefore, we examined the number of days in the observed record and in the generated series for which T_{min} is at or below freezing (0°C). As shown in Figure 4a, the spectral weather generator replicates the mean annual number of freeze events within 10 days, although differences are much smaller for most stations and ENSO phases (Figure 4a). Differences in the observed and generated number of freeze events are slightly larger for the AR generator (up to nearly 13 days, Figure 4a), and are statistically significant at α=0.05 at three stations (Andalusia during the cold ENSO phase, Anniston and Tallahassee during the neutral ENSO phase). On a monthly basis, results from both weather generators agree with observations for months with more than about 6-7 freeze events. For months with fewer freeze events, both approaches tend to slightly overestimate the number of freeze events (Figure 4). Results from the spectral generator exhibit slightly better agreement with observations than the AR model during the neutral and warm ENSO phases.

For some applications, it may be necessary for generated data to reproduce higher order statistics, such as skewness. While weather generators utilizing Gaussian representation of temperatures will not produce skewed data (Harmel et al. 2002), Figure 5a confirms that the spectral model replicates the mean observed T_{min} skewness better than the AR model, which rarely produces absolute skewness values greater than 0.5. Although the skewness values generated with the spectral model are more similar to observed skewness values, they are still lower than observed values and do not exhibit the same level of variability in skewness found in the observed data. A weather generator based on resampling techniques introduced by Clark et al. (2004) produced similar results.

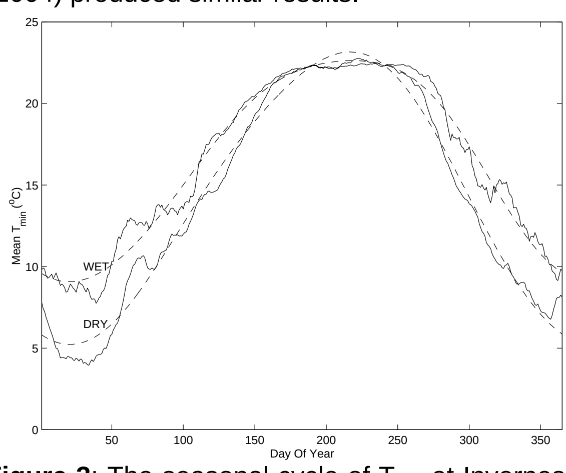

Figure 3: The seasonal cycle of T_{min} at Inverness, FL. Solid lines represent 15-day moving averages of the daily means. Dashed lines represent the 3-harmonic fit used to characterize the seasonal cycle in the AR model.

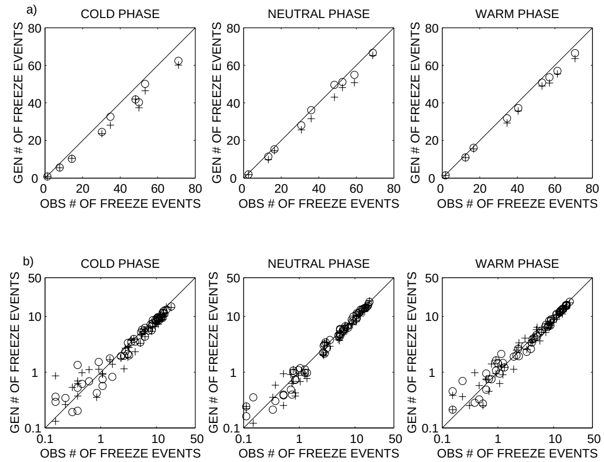

Figure 4: Mean number of a) annual and b) monthly freeze events across all stations for each ENSO phase. Circles (o) represent the spectral weather generator while pluses (+) represent the autoregressive weather generator.

4.4. Diurnal Temperature Range (DTR)

The spectral weather generator adequately replicates the mean daily DTR over the entire year and individual calendar months. At the annual timescale, differences between observed and generated mean daily DTR are less than 0.1°C, while monthly differences are slightly larger, but not statistically significant (at α=0.05), ranging from 0.2-0.6°C. Annual mean daily DTR produced by the Richardson weather generator also exhibits good agreement with observations.

Differences in monthly means range from 0.3-0.8°C and are statistically significant for a single month and ENSO phase at six stations (Anniston, Tallahassee, and Eastman during August of the cold ENSO phase, Haleyville during March of the neutral ENSO phase, Moore Haven during September of the neutral ENSO phase, and Athens during December of the neutral ENSO phase). The standard deviation of daily DTR from the spectral weather generator also exhibits excellent agreement with observations, while statistically significant differences occur at two stations for a single month (Moore Haven during August of the warm ENSO phase and Eastman during August of the cold ENSO phase) for the AR model.

As with T_{min}, we also consider statistics describing the distribution of the monthly mean DTR. At the monthly timescale, both weather generators produce mean monthly mean DTR values that are similar to those observed, although DTR values produced by the AR weather generator are significantly different from those observed for a single station and ENSO phase (Athens, GA during neutral ENSO December).

The interannual variability of annual mean DTR exhibits similar behavior to that described for T_{min} and both weather generators underestimate the interannual variance which is usually less than 1°C. Interannual variability of the monthly means is better captured by the spectral weather generator, and although interannual variability is still slightly underestimated, application of an F-test with α=0.05 does not result in a rejection of the null hypothesis that generated and observed interannual variances are equal for any station, month, or ENSO phase. For some stations and ENSO phases, the AR model produces monthly interannual variances that are only 1/3 to 1/2 the size of observed interannual variances and are thus deemed statistically significant by an F-test with α=0.05.

Previous studies have indicated that AR weather generators sometimes produce negative DTR (i.e., $T_{min} > T_{max}$). To investigate this within the context of our study, we counted the occurrences of this fundamental error within a 100-year simulation. The results varied widely, ranging from only 4 occurrences (at Moore Haven, FL during the cold ENSO phase) to 177 occurrences (at Anniston, AL during the neutral ENSO phase). These errors are not present in the spectral weather generator, due to the model formulation characteristics.

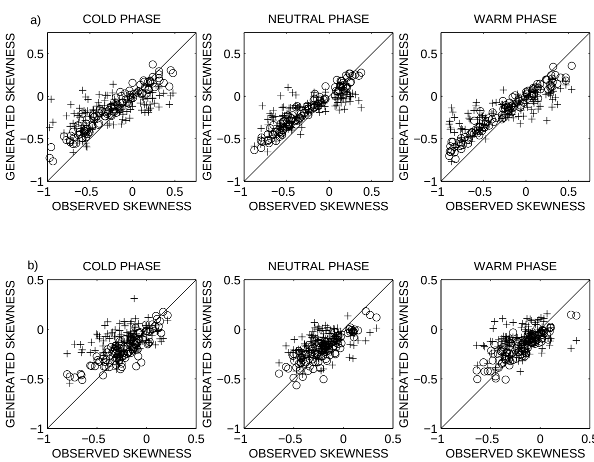

Figure 5: Mean monthly skewness of daily a) T_{min} and b) DTR across all stations for each to ENSO phase. Circles (o) represent the spectral weather generator while pluses (+) represent the autoregressive weather generator.

5. SUMMARY AND CONCLUSIONS

We have combined existing methods for generating daily precipitation with an innovative spectral approach to generating daily minimum air temperature and diurnal temperature range. The spectral weather generator was applied to data from nine stations in the southeast USA and the generated data was compared to both observed data and data generated by a variant of the commonly used autoregressive weather generator.

Evaluation of the generated precipitation data revealed that both the mean number of wet days and the mean precipitation amount were adequately simulated across a range of timescales but that variability was generally underestimated, in agreement with previous studies. These results suggest that, even within a particular ENSO phase, weather generators may benefit from inclusions of parameters which can better characterize low frequency variability.

Our analysis of temperatures generated by the spectral and autoregressive weather generators identified several advantages of using spectral method for generating daily temperatures. The spectral generator resulted in fewer rejections of null hypotheses concerning equality of means and variances of T_{min} and DTR across multiple timescales and also replicated observed skewness and freeze event occurrence on both annual and monthly timescales better than the AR model, particularly for the southernmost stations. This finding has particular relevance for agricultural modeling applications where freeze events are critical for many types of crops. Lastly, the spectral generator alleviates the problem of simulating negative DTR, a fundamental simulation error. The implications of these findings will vary depending on the particular weather generator application, but our findings suggest that the spectral weather generator produces temperatures that are more realistic than those produced by the autoregressive approach and should therefore be more appropriate for most weather generator applications.

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