STOCHASTIC MODELING OF THE EFFECTS OF LARGE-SCALE CIRCULATION ON DAILY WEATHER IN THE SOUTHEASTERN U.S.

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Abstract. Statistical methodology is devised to model time series of daily weather at individual locations in the southeastern U.S. conditional on patterns in large-scale atmosphere–ocean circulation. In this way, weather information on an appropriate temporal and spatial scale for input to crop–climate models can be generated, consistent with the relationship between circulation and temporally and/or spatially aggregated climate data (an exercise sometimes termed 'downscaling'). The Bermuda High, a subtropical Atlantic circulation feature, is found to have the strongest contemporaneous correlation with seasonal mean temperature and total precipitation in the Southeast (in particular, stronger than for the El Niño–Southern Oscillation phenomenon). Stochastic models for time series of daily minimum and maximum temperature and precipitation amount are fitted conditional on an index indicating the average position of the Bermuda High. For precipitation, a multi-site approach involving a statistical technique known as 'borrowing strength' is applied, constraining the relationship between daily precipitation and the Bermuda High index to be spatially the same. In winter (the time of greatest correlation), higher daily maximum and minimum temperature means and higher daily probability of occurrence of precipitation are found when there is an easterly shift in the average position of the Bermuda High. Methods for determining aggregative properties of these stochastic models for daily weather (e.g., variance and spatial correlation of seasonal total precipitation) are also described, so that their performance in representing low frequency variations can be readily evaluated.

1. Introduction

Many apparent connections between patterns in large-scale atmosphere–ocean circulation and climate in the southeastern U.S. have been noted in the literature. Prominent enough to be cited in studies ranging from national to global in scope is a tendency for winters to have below average temperature and above average precipitation during El Niño–Southern Oscillation (ENSO) warm phase events (Kiladis and Diaz, 1989; Ropelewski and Halpert, 1986). The climate in the Southeast has also been linked to the hemispheric-scale circulation, including the Pacific/North American (PNA) pattern (Leathers et al., 1991) and the North Atlantic Oscillation

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(NAO) (Rogers, 1984), and to features of the Atlantic subtropical circulation such as the Bermuda High (BH) (Stahle and Cleaveland, 1992).

One reason for focusing on the Southeast is that effects of large-scale circulation, particularly the ENSO phenomenon, have been detected in crop yields; for instance, corn yields tend to be higher during ENSO cold phase events (Hansen et al., 1998, 1999). These impacts on crop yields have also been quantified indirectly through use of mechanistic crop models such as EPIC (Erosion Productivity Impact Calculator; Williams et al., 1989) (Izaurralde et al., 1999; Legler et al., 1999). In related work, Peters et al. (2003) found that a vegetation index, derived from remotely sensed data for the Southeast, has a negative response to ENSO warm phase events. Crop yield can be viewed as a complex integrator of weather over time. In fact, typical crop–climate models require weather inputs on a daily time scale, including minimum and maximum temperature and precipitation amount. Streamflow, another integrator of weather (especially precipitation) over both space and time, tends to be enhanced in the Gulf of Mexico region during ENSO warm phase events (Kahya and Dracup, 1993).

The purpose of the present paper is to statistically model the relationship between daily weather at individual locations in the Southeast and large-scale atmosphere–ocean circulation. The methodology involves fitting stochastic weather generators (e.g., Parlange and Katz, 2000; Richardson, 1981; Wilks and Wilby, 1999) conditional on circulation indices (Katz and Parlange, 1993, 1996; Woolhiser et al., 1993). Because of difficulties in detecting the weaker circulation signal in precipitation, the statistical technique known as 'borrowing strength' is applied (Tukey, 1961). This multi-site approach involves constraining the effect of the circulation index on a daily weather statistic to be the same at all locations within a specified region.

Among the indices of the BH, NAO, ENSO, and PNA averaged seasonally, the one having the strongest contemporaneous correlation with seasonal total precipitation and mean minimum and maximum temperature at eight locations in the Southeast is identified. The statistical methodology is then applied to model the relationship between the selected index and time series of daily minimum and maximum temperature and precipitation amount at the same locations. Through this statistical approach, weather data on an appropriate temporal and spatial scale for input to crop–climate models can be produced, consistent with the relationship between the circulation index and seasonally aggregated climate data (an exercise sometimes termed 'downscaling'; Wilby and Wigley, 1997). Methods for determining aggregative properties of these stochastic models for daily weather (e.g., variance and spatial correlation of seasonal total precipitation as aggregated from daily weather generated by these models) are also described.

Table I

List of acronyms for atmosphere–ocean circulation features and indices

Feature	Acronym
Bermuda pressure	BER
Bermuda High	BH
Bermuda High index	BHI
El Niño–Southern Oscillation	ENSO
North Atlantic Oscillation	NAO
New Orleans pressure	NO
New Orleans pressure index	NOI
Pacific/North Atlantic pattern	PNA
Southern Oscillation	SO

2. Background

Several studies have specifically focused on connections between temporally and/or spatially aggregated climate in the Southeast and large-scale atmosphere–ocean circulation patterns (Table I lists acronyms for circulation features). Upon closer examination, the link between ENSO and temperature and precipitation mentioned in the Introduction actually appears to be somewhat limited in extent both temporally (i.e., only during winter season) and spatially (i.e., only for part of Florida, as well as other portions of the Gulf Coast). In a systematic study of the relationship between large-scale circulation and precipitation in the Southeast, Henderson and Vega (1996) found a statistically significant correlation with ENSO only in Florida and only during the winter. In their study of precipitation during the spring in the southeastern coastal states of Georgia, North Carolina, and South Carolina, Stahle and Cleaveland (1992) did not detect any statistically significant correlation with ENSO. Neither did Downton and Miller (1993) for winter mean (or minimum) temperature averaged over central Florida.

Warmer than normal winters tend to occur in the Southeast with strong zonal flow over the North Atlantic, a possible connection to the NAO (Rogers, 1984). For instance, Downton and Miller (1993) obtained statistically significant correlations between winter mean (or minimum) temperature averaged over central Florida and the NAO. But no connection to precipitation in the Southeast has been identified, with Henderson and Vega (1996) finding essentially no correlation. Likewise, Stahle and Cleaveland (1992) did not detect any correlation between the NAO and spring precipitation in the southeastern coastal states (not including Florida).

Lower (higher) than normal temperatures over the Southeast are associated with a meridional (zonal)-like flow pattern over the continental U.S., particularly in winter, a possible link to the PNA (Leathers et al., 1991). For example, Downton and Miller (1993) obtained statistically significant correlations between winter mean (or minimum) temperature averaged over central Florida and the PNA. For precipitation, any relationship to PNA is anticipated to be weaker and primarily in winter, with meridional flow being associated with lower than normal precipitation inland (i.e., west of the Appalachian Mountains), but not necessarily in coastal areas (i.e., east of the Appalachians) where the relationship might even be reversed (Leathers et al., 1991). In particular, Henderson and Vega (1996) obtained a statistically significant negative correlation between the PNA and winter precipitation for the inland ('North Central') portion of the Southeast, but a positive correlation for Florida, and otherwise no relationship along the East Coast. Stahle and Cleaveland (1992) could not find any connection between the PNA and spring precipitation for the southeastern coastal states (not including Florida).

In attempts to identify sources of low frequency variations in the climate of the Southeast, features of the Atlantic subtropical circulation have recently received some consideration as well. One such feature is the BH or North Atlantic subtropical anticyclone (Davis et al., 1997). Stahle and Cleaveland (1992) provided evidence that spring precipitation in the southeastern coastal states (not including Florida) is lower (higher) than normal if the western edge of the subtropical high is west (east) of its average position. Henderson and Vega (1996) found more robust correlations between seasonal total precipitation and the BH than with ENSO, NAO, or PNA, the relationship always being statistically significant irrespective of season or subregion of the Southeast. Connections to the temperature in the Southeast have received less attention, but Henderson and Muller (1997) did suggest that temperature extremes in the adjacent South Central region of the U.S. are related to the BH.

Although much research has been devoted to the relationship between large-scale atmosphere–ocean circulation and spatial and/or temporally aggregated climate, not nearly as much work has been conducted on the corresponding relationships to daily weather data at individual sites, whether for the Southeast or elsewhere. Usually, the approach has been to let the data 'speak for themselves' (e.g., Legler et al., 1999). That is, the daily weather observations are 'composited' according to a categorization of circulation patterns (e.g., El Niño, neutral, and La Niña events), without an explicit examination of the circulation effects on these scales. The limitations of this approach relate to the non-uniqueness in disaggregation (or downscaling). For instance, does a decrease in monthly or seasonal precipitation correspond to fewer storms, less intense storms, or both?

A few studies have directly examined the relationship between circulation and daily weather statistics. For example, Wettstein and Mearns (2002) found relationships between the NAO and daily minimum and maximum temperature statistics in the northeastern U.S. and Canada. Through resampling, Thompson and Wallace (2001) established statistically significant links between the NAO and daily weather statistics at locations across the Northern Hemisphere. A more systematic approach consists of fitting a stochastic model to time series of daily weather conditional on the state of a circulation index. This approach was followed by Katz and Parlange (1993) in modeling daily precipitation at individual locations in California conditional on a pressure index and by Woolhiser et al. (1993) in modeling daily precipitation at individual locations in the southwestern U.S. conditional on ENSO. Subsequent applications include Grondona et al. (2000) to model the relationship between ENSO and daily precipitation at stations in Argentina and Uruguay and Kiely et al. (1998) to model daily precipitation at a site in Ireland conditional on pressure or wind direction.

3. Data and Seasonal Statistics

3.1. DATA

Figure 1 shows the eight locations across the Southeast for which climate data were obtained, with the station names (and abbreviations) and period of record being listed in Table II. It should be noted that only one of these locations is in Florida or near the Gulf Coast. All these sites are first-order stations (as classified by the U.S. National Weather Service), with the advantage of high quality measurements (in particular, not much missing data; see Table II for percentage missing data), but the disadvantage of possible urban influences (e.g., heat island effect). The daily weather variables considered are minimum and maximum temperature (°C) and precipitation amount (mm), with a 'trace' (i.e., a positive amount smaller than 0.005 in ($\approx$0.13 mm)) being treated as a zero amount. Seasonal means and totals are obtained by aggregating the daily data over the appropriate time period, with the seasonal statistic being computed if three or less days of observations within the season are missing (otherwise the seasonal value is treated as missing).

To reflect low frequency variation, each circulation measure is aggregated to a single seasonal value. The source of the data for the BH circulation measure is the gridded monthly mean sea level pressure from the NCAR/NCEP reanalysis (http://www.cgd.ucar.edu/cas/catalog/nmc/rean/press/means.html; Kalnay et al., 1996). The approach of Stahle and Cleaveland (1992) was followed, with an exploratory analysis in which the pressure at each of the individual grid points in a region that spans the eastern U.S., Gulf of Mexico, and western Atlantic Ocean was considered as a candidate. Two grid points were selected: one at 30° N, 90° W (near New Orleans), the second at 32.5° N, 65° W (near Bermuda) (denoted by NO and BER, respectively; see Figure 1). The New Orleans grid point is the same as, and the one for Bermuda slightly different from, those selected by Stahle and Cleaveland (1992).

A seasonal measure of the BH is constructed by first aggregating the monthly mean pressure to seasonal means and then taking the difference (Bermuda minus New Orleans). This measure effectively indicates the approximate position of the

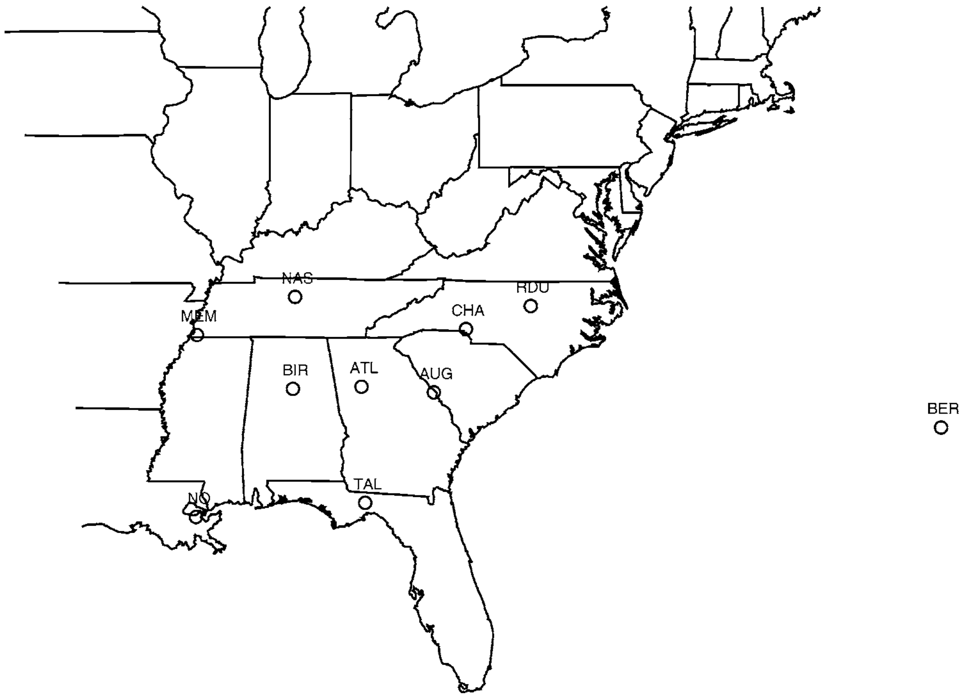

Figure 1. Map of southeastern U.S. showing eight sites of daily weather data, as well as two pressure grid locations on which BH based.

Table II

List of abbreviations for stations and characteristics of climate data record for winter season (e.g., winter 1959 = December 1958–February 1959)

Site	Abbrev.	Time period	Missing data (%)		
			Min. temp.	Max. temp.	Prec.
Atlanta, GA	ATL	1959–1996	0	0	0
Augusta, GA	AUG	1959–1996	0	0	0
Birmingham, AL	BIR	1959–1996	1.8	1.8	2.8
Charlotte, NC	CHA	1959–1996	0	0	0
Memphis, TN	MEM	1959–1996	0	0	0
Nashville, TN	NAS	1959–1996	0.8	0.8	0.8
Raleigh–Durham, NC	RDU	1959–1995	0	0	0
Tallahassee, FL	TAL	1959–1995	0	0	0.1

western edge of the Atlantic subtropical high, with higher values indicating a location farther east than normal. In most of the subsequent analyses, the BH will be converted into a simpler two-state index denoted by BHI (i.e., BHI = 1 if BH > median, BHI = 0 otherwise). The pressure at New Orleans alone (NO) will also be used as a circulation measure, somewhat cruder but still related to the position of the subtropical high (in this case, higher values indicate a location farther west than normal). The corresponding two-state index is denoted by NOI (i.e., NOI = 1 if NO > median, NOI = 0 otherwise).

Three other circulation measures are considered: (i) an index of the NAO based on the difference in standardized seasonal mean sea level pressure between Ponta Delgada, Azores and Stykkisholmur/Reykjavik, Iceland (source: http://www.cgd.ucar.edu/~jhurrell/nao.html; Hurrell, 1995); (ii) an index of the PNA derived from the standardized 500 hPa geopotential heights at four grid points (i.e., 20° N, 160° W; 45° N, 165° W; 55° N, 115° W; 30° N, 85° W) across the Pacific Ocean and North America, including one in northern Florida (source: http://tao.atmos.washington.edu/data_sets/pna/; Wallace and Gutzler, 1981); and (iii) an index of the Southern Oscillation (SO) based on the difference in standardized seasonal mean sea level pressure between Tahiti and Darwin (source: http://www.cpc.ncep.noaa.gov/data/indices/index.html; Trenberth, 1984).

3.2. SEASONAL STATISTICS

Tables III–V list the sample correlations between the circulation indices and winter mean minimum and maximum temperature and total precipitation at the southeastern sites. These correlations are presented only for the winter season, the time of the year in which they are greatest (although spring and summer seasons would be more important for most crops). To check for time trends, the variable ‘Year’ is included in the tables as well.

The sample correlations of winter temperature with the BH are all statistically significant at the 5% level, being of a similar magnitude for both the mean minimum and maximum (Tables III and IV). But for the NO, all of the correlations with the maximum and all but two with the minimum are statistically insignificant. In all cases for the NAO and at all but one location for the PNA, the correlations with both the minimum and maximum are statistically significant, but they are systematically smaller in magnitude than the corresponding ones for the BH. The SO performs worst of all the circulation indices for the minimum temperature, with all correlations being statistically insignificant, and second worst to the NO for the maximum, with all but one being insignificant. Linear time trends for minimum temperature are statistically significant at several locations, most likely associated with the urban heat island. Nevertheless, these temperature–circulation correlations do not change much if a linear trend is removed from the temperature time series. For this reason, the temperature time series are not de-trended in subsequent analyses.

Table III

Correlation between circulation indices (as well as time trend) and winter mean minimum temperature at eight locations in Southeast (a correlation of about 0.32 or greater in absolute value is statistically significant at the 5% level)

Site	BH	NO	NAO	PNA	SO	Year
ATL	0.661	–0.179	0.604	–0.340	–0.042	0.432
AUG	0.785	–0.314	0.455	–0.492	0.031	0.248
BIR	0.795	–0.380	0.461	–0.586	0.167	0.157
CHA	0.717	–0.212	0.564	–0.426	–0.033	0.458
MEM	0.573	–0.299	0.485	–0.276	–0.082	0.425
NAS	0.713	–0.384	0.525	–0.362	–0.093	0.253
RDU	0.749	–0.290	0.510	–0.473	0.040	0.395
TAL	0.726	–0.293	0.382	–0.500	0.032	0.093

Table IV

Same as Table III except for winter mean maximum temperature

Site	BH	NO	NAO	PNA	SO	Year
ATL	0.636	–0.038	0.633	–0.395	0.171	0.396
AUG	0.689	–0.053	0.474	–0.517	0.242	0.255
BIR	0.734	–0.203	0.505	–0.510	0.262	0.235
CHA	0.651	0.022	0.567	–0.369	0.156	0.245
MEM	0.593	–0.174	0.473	–0.316	0.093	0.292
NAS	0.713	–0.181	0.572	–0.390	0.089	0.166
RDU	0.727	–0.110	0.531	–0.494	0.185	0.272
TAL	0.736	–0.181	0.530	–0.646	0.335	0.296

For winter total precipitation (Table V), the sample correlations with the BH are not as great as for temperature, but still statistically significant for the 'inland' half of the stations (i.e., Atlanta, Birmingham, Memphis, and Nashville). If the NO pressure alone is used instead, then the correlations with the remaining 'coastal' half of the stations (i.e., Augusta, Charlotte, Raleigh–Durham, and Tallahassee) are at least borderline statistically significant. The pattern in the precipitation correlations with the PNA resembles that for the BH (if the sign is reversed), most being smaller in magnitude but still attaining at least borderline statistical significance at the inland locations. The precipitation correlations with the NAO and

Table V
Same as Table III except for winter total precipitation

Site	BH	NO	NAO	PNA	SO	Year
ATL	0.522	–0.422	0.185	–0.277	0.111	–0.148
AUG	0.235	–0.480	–0.008	0.107	–0.181	–0.156
BIR	0.401	–0.406	0.028	–0.387	0.239	–0.210
CHA	0.341	–0.385	0.086	–0.183	0.021	–0.162
MEM	0.493	–0.088	0.277	–0.419	0.036	0.185
NAS	0.375	–0.166	0.121	–0.430	0.109	–0.055
RDU	0.260	–0.310	0.056	–0.040	–0.029	–0.039
TAL	0.098	–0.280	–0.282	0.023	–0.241	–0.133

SO are all statistically insignificant, although a few for the NAO attain borderline significance. There is no evidence of a trend in precipitation.

To examine the conditional distribution of seasonally aggregated climate, the two-state BHI and NOI are used. Figures 2–5 show boxplots of the conditional distribution of minimum and maximum winter mean temperature given the BHI state (for ease of display the stations are divided into the inland and coastal groups). Although the conditional median is higher at all eight locations given BHI $= 1$, a consistent effect is not evident for variability, as measured in terms of the interquartile range (i.e., height of box) (plus the shifts in the conditional standard deviation are not always in the same direction as for the interquartile range). For winter total precipitation, both the conditional median and interquartile range are higher at the four inland locations given BHI $= 1$ (Figure 6); likewise, at the four coastal locations given NOI $= 0$ (Figure 7). In summary, warmer and wetter than normal conditions on the average (along with higher precipitation variability) during the winter in the Southeast tend to be associated with the western edge of the Atlantic subtropical high being east of its average position. The statistical significance of these apparent effects will be evaluated more systematically in Sections 4 and 5.

Table VI lists the sample correlations between the different atmospheric–ocean circulation indices in winter. The BH has statistically significant correlations with the NAO and PNA, but not with the SO. The correlation between the pressure at the two grid points, BER and NO, on which the BH is based is not statistically significant, with the BH itself being more strongly related to the BER than to the NO. The only statistically significant trend is for the NAO, whose apparent non-stationarity has been noted in the literature (Hurrell, 1995).

Making use of multiple regression analysis, the inclusion of the SO (or other circulation variables) as an additional predictor, along with the BH, generally does not result in a statistically significant improvement in the fit to seasonal temperature or precipitation. Likewise, replacing the BH with the two gridded pressure

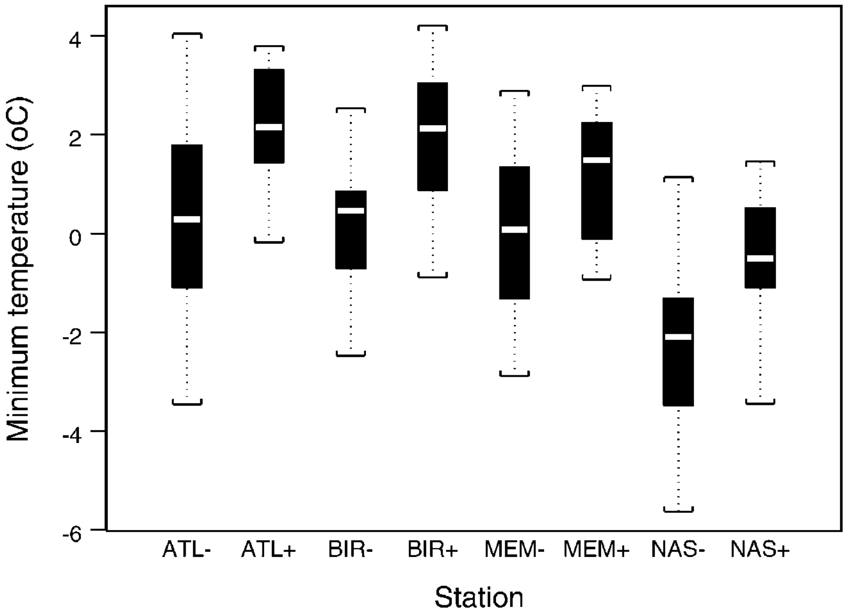

Figure 2. Boxplots (i.e., sample minimum, lower quartile, median, upper quartile, and maximum) of conditional distribution of winter mean minimum temperature at four inland locations given state of BHI (BHI = 1 indicated by '+' after station abbreviation, BHI = 0 by '–').

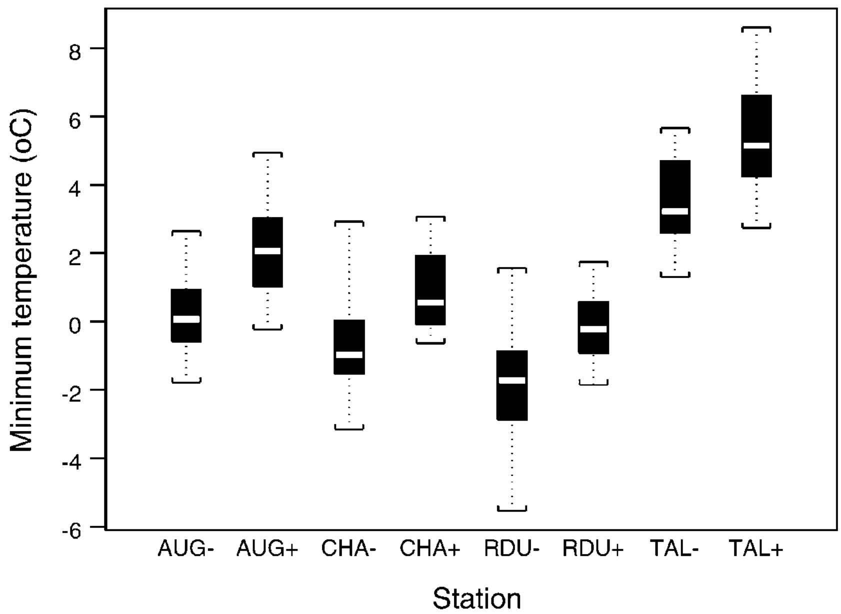

Figure 3. Same as Figure 2 except at four coastal locations.

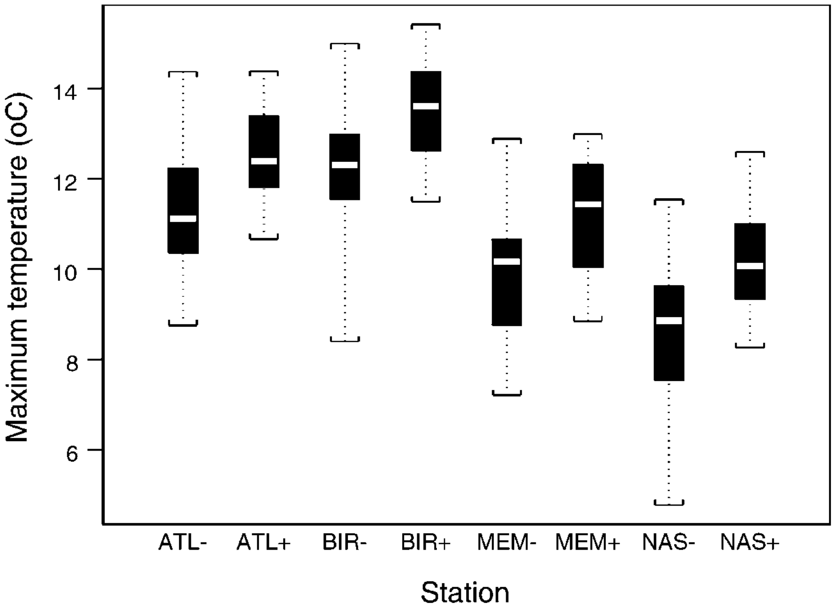

Figure 4. Boxplots of conditional distribution of winter mean maximum temperature at four inland locations given state of BHI.

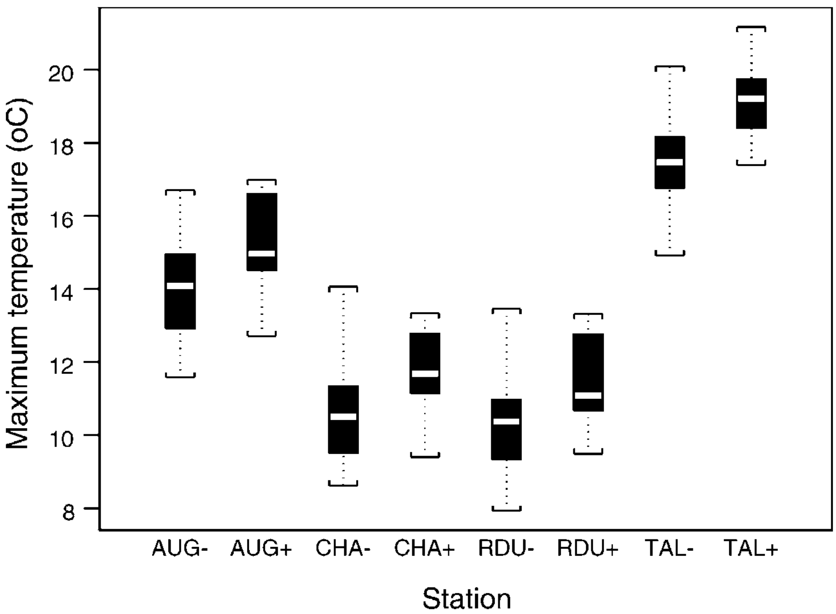

Figure 5. Same as Figure 4 except at four coastal locations.

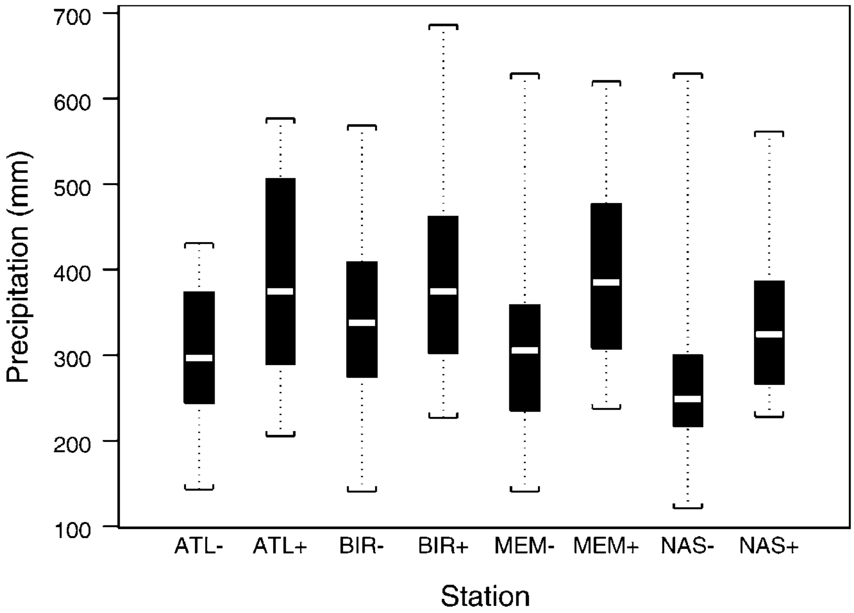

Figure 6. Boxplots of conditional distribution of winter total precipitation at four inland locations given state of BHI.

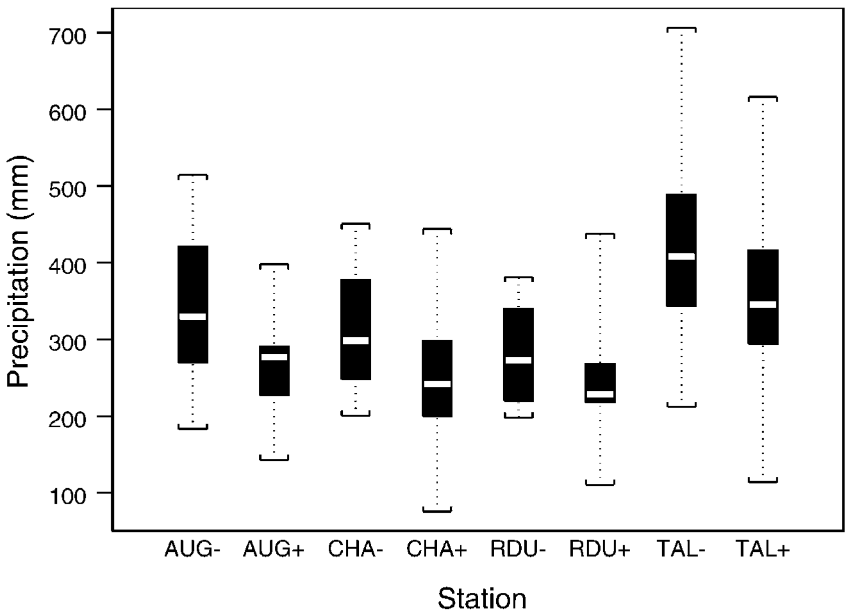

Figure 7. Same as Figure 6 except at four coastal locations given state of NOI.

Table VI

Correlations between circulation indices in winter (a correlation of about 0.32 or greater in absolute value is statistically significant at the 5% level)

Index	Year	BER	BH	NO	NAO	PNA
BER	0.166	–	–	–	–	–
BH	0.040	0.781	–	–	–	–
NO	0.177	0.221	–0.437	–	–	–
NAO	0.427	0.656	0.475	0.203	–	–
PNA	0.103	–0.504	–0.565	0.157	0.011	–
SO	–0.156	0.309	0.220	0.102	0.051	–0.402

variables, BER and NO (or introducing BER into the regression along with the NO in the case of seasonal precipitation for the coastal sites), usually produces only marginal improvements in the fit. Consequently, the subsequent analyses of time series of daily weather are restricted to conditioning on only the BHI or NOI.

4. Daily Temperature: Single-Site Approach

Stochastic weather generators typically model the minimum and maximum temperature at the same site as a bivariate time series, incorporating both the cross correlation on the same day and the serial correlation from one day to the next. Usually, dependence between temperature and precipitation is introduced by shifting the temperature means and standard deviations conditional on precipitation occurrence (e.g., Richardson, 1981). In the present paper, to simplify matters the daily minimum and maximum temperature are analyzed separately, with no dependence on precipitation occurrence. The temperature is treated at one location at a time, conditioning on the two-state BHI and focusing on the winter season.

4.1. METHODS

Let $\{X_t, t = 1, 2, \ldots, T\}$ denote the time series of daily temperature (either minimum or maximum) during a given season of length T days in a particular year at a single location. This time series is assumed stationary (i.e., the annual cycle is assumed small enough to ignore within a season). The temporal dependence structure of daily temperature is modeled as a first-order autoregressive [AR(1)] process, but with the parameters varying with the BHI state. Given BHI $= i$, the daily temperature time series is assumed to be an AR(1) process with conditional mean

μ_i, standard deviation σ_i, and first-order autocorrelation coefficient ϕ_i, $i = 0, 1$. That is, the temperature today X_t is related to the temperature yesterday X_{t-1} by

$$X_t = \mu_i + \phi_i(X_{t-1} - \mu_i) + \sigma_a(i)a_t\,, \quad a_t \sim N(0, 1). \tag{1}$$

Here the error component a_t is serially uncorrelated and has a standard normal distribution (denoted by $N(0, 1)$ in (1)). The standard deviation σ_i of the temperature variable is related to the standard deviation of the error component $\sigma_a(i)$ of the AR(1) process by

$$\sigma_i^2 = \sigma_a^2(i)/(1 - \phi_i^2) \tag{2}$$

(e.g., Mearns et al., 1984). The assumption that, conditional on BHI, the daily temperature time series can be modeled as an AR(1) process is not as restrictive as it might appear. Unconditionally, such an approach induces a model for daily temperature that is more complex than AR(1) (Katz and Parlange, 1996).

Special cases of the dependence of these AR(1) parameters on the BHI can be fitted by this modeling approach, ranging from 'no effect' to 'full effect', by imposing the following constraints in (1):

(i) *no effect* [$\mu_0 = \mu_1, \sigma_a(0) = \sigma_a(1), \phi_0 = \phi_1$]
(ii) *mean effect* [$\sigma_a(0) = \sigma_a(1), \phi_0 = \phi_1$]
(iii) *mean and variance effect* ($\phi_0 = \phi_1$)
(iv) *full effect* (no constraints).

A description of the methodology involved in fitting such models appears in Appendix A. In essence, the approach uses multiple regression analysis with least squares parameter estimation to fit (1) under the constraints imposed by models (i)–(iv). In this way, the autocorrelation of the temperature time series is explicitly taken into account.

Which of these alternative forms of model best fits the data is decided on the basis of the Bayesian information criterion (BIC) (see Appendix A). This technique balances the improved fit of more complex models against the need to estimate additional parameters (Schwarz, 1978). According to this criterion, the model with the smallest BIC value is preferred.

4.2. RESULTS

The assumption that the minimum and maximum temperature time series are stationary within the winter is indirectly examined through the comparison of boxplots for the distribution of the corresponding monthly means. Figure 8 shows these boxplots for the months of December, January, and February at Atlanta. On average, January is the coolest of the three months, February the warmest. No pattern in variability, as measured by the interquartile range, is evident. Similar patterns in monthly mean minimum and maximum temperature during the winter are evident in the boxplots (not shown) for the other locations. By allowing some

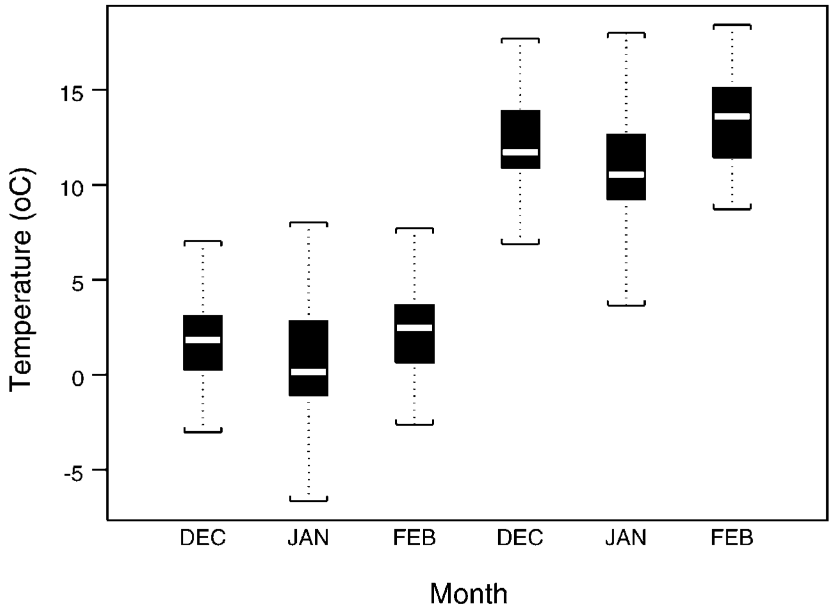

Figure 8. Boxplots of distribution of monthly mean minimum and maximum temperature during winter at Atlanta.

of the parameters in (1) to depend on the time of year, it would be straightforward to introduce annual cycles into the methodology described in Section 4.1.

Tables VII and VIII list the sample conditional mean, standard deviation, and first-order autocorrelation coefficient for the daily time series of minimum and maximum temperature in winter at the eight locations in the Southeast. For the minimum temperature (Table VII), the conditional mean is 1–2 °C higher when BHI = 1, whereas the shifts in conditional standard deviation and autocorrelation are relatively small and inconsistent in direction. For the maximum temperature (Table VIII), the increases in conditional mean when BHI = 1 generally are only slightly smaller than the corresponding ones for the minimum temperature. The daily time series of minimum and maximum temperature possess substantial sample autocorrelations, usually between 0.6 and 0.7.

Tables VII and VIII include a summary of the results of applying the model fitting and selection procedure to the winter daily time series of minimum and maximum temperature at the eight locations in the Southeast. With only two exceptions, the BIC selects model (ii) (i.e., varying the mean with the BHI state) as best. For the maximum temperature at Charlotte and Raleigh–Durham, model (iii) (i.e., varying both the mean and variance) is selected instead. In no case is model (i) (i.e., no effect) or model (iv) (i.e., varying the mean, variance, and autocorrelation) selected.

How the model selection criterion performs in practice is demonstrated for the example of the daily maximum temperature in winter at Atlanta. The BIC values

Table VII
Conditional mean, standard deviation, and autocorrelation of winter daily minimum temperature at eight locations in Southeast given state of BHI

Site	Mean (°C)		Std. dev. (°C)		Autocorrelation	
	BHI = 0	BHI = 1	BHI = 0	BHI = 1	BHI = 0	BHI = 1
ATL	0.4 [a]	2.1 [a]	5.85	5.60	0.724	0.709
AUG	0.3 [a]	2.1 [a]	5.62	5.74	0.624	0.656
BIR	0.3 [a]	1.9 [a]	6.25	6.31	0.650	0.664
CHA	–0.7 [a]	0.9 [a]	5.41	5.41	0.688	0.655
MEM	0.1 [a]	1.2 [a]	6.16	6.04	0.702	0.683
NAS	–2.3 [a]	–0.5 [a]	6.61	6.52	0.692	0.680
RDU	–1.7 [a]	0.0 [a]	5.84	5.71	0.671	0.615
TAL	3.6 [a]	5.5 [a]	6.30	6.55	0.657	0.697

[a] Vary with BHI state (according to BIC).

Table VIII
Same as Table VII except for winter daily maximum temperature

Site	Mean (°C)		Std. dev. (°C)		Autocorrelation	
	BHI = 0	BHI = 1	BHI = 0	BHI = 1	BHI = 0	BHI = 1
ATL	11.3 [a]	12.5 [a]	6.05	5.91	0.668	0.661
AUG	14.1 [a]	15.3 [a]	5.79	5.98	0.650	0.650
BIR	12.1 [a]	13.4 [a]	6.21	6.13	0.674	0.660
CHA	10.5 [a]	11.8 [a]	5.77 [a]	5.94 [a]	0.659	0.629
MEM	10.0 [a]	11.1 [a]	6.93	6.81	0.687	0.658
NAS	8.6 [a]	10.2 [a]	6.99	6.95	0.678	0.633
RDU	10.2 [a]	11.5 [a]	6.14 [a]	6.36 [a]	0.637	0.613
TAL	17.4 [a]	19.1 [a]	5.15	5.13	0.623	0.652

[a] Vary with BHI state (according to BIC).

for all four candidate models are listed in Table IX, with the model having the smallest value only varying the mean with the BHI, the second-best model varying both the mean and variance. The model with no dependence on the BHI is ranked as better than the one with full dependence. For the minimum temperature at Atlanta, a similar ordering of BIC values is obtained, except that the model with no dependence on the BHI is ranked the worst. The mean and variance effect model ranks second best for both the minimum and maximum temperature in nearly all cases at the other locations.

Table IX
Model selection for winter daily maximum temperature at Atlanta ($m = 38$ yr)

Model	Number parameters	Error variance (°C)^2 BHI = 0	BHI = 1	BIC
No effect	3	20.102	20.102	10,189.7
Mean effect	4	20.053	20.053	10,185.0 [a]
Mean and variance effect	5	20.254	19.851	10,188.4
Full effect	6	20.253	19.850	10,192.0

[a] Minimum.

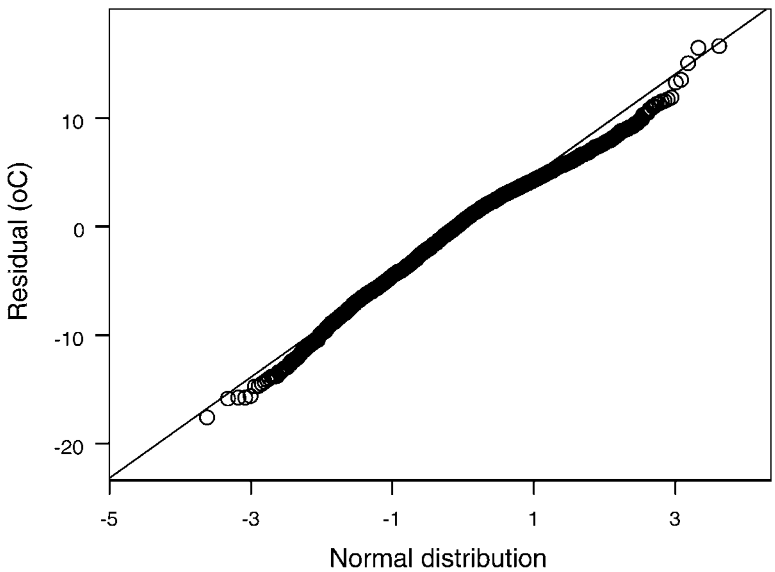

Figure 9. Q–Q plot of residuals for winter daily maximum temperature at Atlanta, along with straight line.

To check the assumption that the error term in (1) is normally distributed, quantile–quantile (Q–Q) plots are constructed. For the daily maximum temperature in winter at Atlanta, Figure 9 shows a Q–Q plot of the residuals (i.e., estimated error terms) for the model in which only the mean depends on the BHI (i.e., the model selected by the BIC). Because the plot is approximately linear, the assumption of normality appears reasonable. For the Atlanta minimum temperature, the linearity of the Q–Q plot (not shown) is less clear, with some evidence of a departure from normality in the extreme lower and upper tails of the distribution. Similar patterns are evident in the Q–Q plots (not shown) for the other locations, with the normal approximation being better for the maximum than for the minimum temperature.

5. Daily Precipitation: Multi-Site Approach

The analysis of the effects of circulation on daily precipitation is complicated by several factors. For one thing, the intermittency of the precipitation process necessitates separate treatment of two component processes, the occurrence and intensity. There is no way of anticipating whether effects of the BH (or NO) on seasonal total precipitation correspond to effects on the daily occurrence alone, the daily intensity alone, or on both. For another, the correlations between the BH (or NO) and seasonal total precipitation are weaker than the corresponding ones for temperature. As will be seen, a single-site analysis of precipitation is not sufficiently powerful to obtain statistical significance when examining these effects on a daily time scale.

5.1. METHODS

Let $\{J_t, t = 1, 2, \ldots, T\}$ denote the time series of daily precipitation occurrence (i.e., $J_t = 1$ indicates a 'wet' day, $J_t = 0$ 'dry' day). This time series is assumed stationary within the winter season. To model the tendency of wet or dry spells to persist, a two-state, first-order Markov chain is assumed as a model for $\{J_t\}$, but with the parameters varying with the BHI or NOI (e.g., Katz and Parlange, 1993). Conditional on circulation index state i, the time series of daily precipitation occurrence is assumed to be a first-order Markov chain with transition probabilities

$$P_{jk}(i) = \Pr\{J_t = k \mid J_{t-1} = j\}, \quad j, k = 0, 1. \tag{3}$$

Let the probability of a wet day be denoted by $\pi_i = \Pr\{J_t = 1\}$ and the first-order autocorrelation coefficient (or 'persistence' parameter) by $d_i = \mathrm{corr}(J_{t-1}, J_t)$, likewise conditional on index state i. These quantities are related to the transition probabilities by

$$\pi_i = P_{01}(i)/(1 - d_i), \quad d_i = P_{11}(i) - P_{01}(i) \tag{4}$$

(e.g., Katz, 1996). The two transition probabilities that appear in (4), $P_{01}(i)$ and $P_{11}(i)$, are sufficient to specify the probabilistic properties of the Markov chain. The assumption that the daily precipitation occurrence time series, given the circulation index, is a first-order Markov chain is not as restrictive as it might appear. Unconditionally, this approach induces a model for daily precipitation occurrence that is more complex than a first-order Markov chain (Katz and Parlange, 1996).

Let $P_{jk}(i, s)$ denote the transition probability defined in (3) at site s, $s = 1, 2, \ldots, S$, where S denotes the total number of sites in the region. The *borrowing strength* approach constrains the effect of the circulation index on the transition probability $P_{jk}(i, s)$ to be the same for all sites within a given region. Specifically, it is assumed that the ratio of the transition probability under the two index states,

$$\Delta_{jk}(s) = P_{jk}(1, s)/P_{jk}(0, s), \tag{5}$$

Table X

Conditional probability of occurrence, transition probabilities, and median intensity for winter daily precipitation at four inland locations given state of BHI

Site	Prob. of occurrence		Transition prob. (P_{01})		Transition prob. (P_{11})		Median intensity (mm)	
	BHI = 0	BHI = 1	BHI = 0	BHI = 1	BHI = 0	BHI = 1	BHI = 0	BHI = 1
ATL	0.324	0.377	0.252	0.295	0.479	0.520	5.59	5.84
BIR	0.312	0.374	0.241	0.293	0.468	0.514	6.86	6.35
MEM	0.296	0.346	0.233	0.278	0.451	0.482	5.59	5.84
NAS	0.327	0.373	0.265	0.296	0.457	0.507	4.83	5.33

is constant, say $\Delta_{jk}(s) = \Delta_{jk}$, for all locations s, $s = 1, 2, \ldots, S$. Such a constraint might well be a plausible approximation in the present circumstances, in which the indices are based on large-scale circulation features. The assumption (5) imposes no constraint on how the precipitation climatology varies across sites (e.g., probability of wet day), only on its relationship with the circulation index. The advantage of this approach is that fewer parameters need to be estimated (e.g., with four locations, conditioning on a two-state index introduces only one additional parameter instead of four for a given transition probability), so that there is a higher chance of detecting an effect that is stable across space.

Details on how to estimate the transition probabilities of the Markov chain model for precipitation occurrence under the constraint (5) are discussed in Appendix B. The BIC is again used to select the appropriate form of conditioning on circulation (see Appendix B). The key requirement is that, conditional on the state of the circulation index, daily precipitation occurrence be spatially independent. The hope is that, if the conditioning variable has a strong enough relationship with precipitation occurrence, then sufficient unconditional dependence would be induced (e.g., Hughes et al., 1999). This assumption will be scrutinized further in Section 6. Instead of (5), an alternative approach would be to impose the constraint in terms of the logistic transformation of precipitation probability (Katz and Parlange, 1995; Stern and Coe, 1984; Woolhiser et al., 1993).

5.2. RESULTS

The assumption that the precipitation occurrence time series is stationary is indirectly examined through the comparison of boxplots for the distribution of the corresponding monthly precipitation totals. Figure 10 shows these boxplots for the months of December, January, and February at Atlanta. No consistent pattern in either the median or the interquartile range is evident, nor in the boxplots (not shown) for the other locations.

Table X includes sample estimates of the conditional probability of occurrence of precipitation and intensity (i.e., precipitation amount on wet days) median in

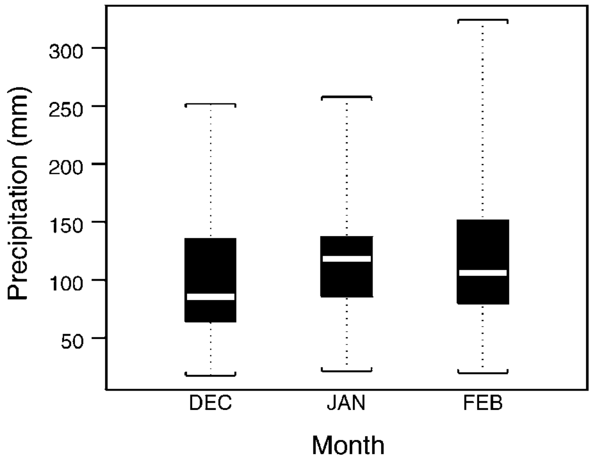

Figure 10. Same as Figure 8 except for total precipitation at Atlanta.

Table XI
Same as Table X except at four coastal locations given state of NOI

Site	Prob. of occurrence		Transition prob. (P_{01})		Transition prob. (P_{11})		Median intensity (mm)	
	NOI = 0	NOI = 1	NOI = 0	NOI = 1	NOI = 0	NOI = 1	NOI = 0	NOI = 1
AUG	0.342	0.299	0.272	0.233	0.481	0.459	6.10	5.08
CHA	0.352	0.301	0.273	0.248	0.497	0.430	5.33	4.83
RDU	0.331	0.304	0.267	0.243	0.461	0.445	5.84	5.08
TAL	0.317	0.273	0.259	0.228	0.444	0.392	8.13	6.60

winter at the four inland locations given the state of the BHI. The estimated probability of a wet day ranges from 14–20% higher when BHI = 1. On the other hand, the shift in the sample median precipitation intensity with the BHI is relatively small and inconsistent in direction. Table XI includes the same statistics at the four coastal locations given the state of the NOI. Consistent shifts in the probability of precipitation are again obtained, being 9–17% higher when NOI = 0. The median intensity is always higher when NOI = 0, with these shifts still being relatively small but somewhat larger in magnitude than those associated with the BHI at the inland locations.

Table X also provides the estimated transition probabilities at the inland locations given the BHI state, with P_{01} and P_{11} being 12–21% and 7–11% higher, respectively, when BHI = 1. Table XI gives the same statistics at the coastal locations conditional on the NOI, with P_{01} and P_{11} being 10–17% and 4–16% higher, respectively, when NOI = 0. Using same methodology as in Katz and Parlange (1993) applied to a single site at a time (i.e., maximum likelihood estimates of transition probabilities and BIC for model selection), these shifts in transition

Table XII

Model selection for winter daily precipitation occurrence at inland locations conditional on BHI ($m = 38$ yr, $S = 4$ sites)

Model	Number parameters	Proportionate effect Δ_{01}	Δ_{11}	BIC
No effect	8	1	1	16,676.5
Borrow strength (P_{01})	9	1.171	1	16,661.3
Borrow strength (P_{11})	9	1	1.091	16,673.3
Borrow strength (P_{01}, P_{11})	10	1.171	1.091	16,658.1 [a]
Full effect	16	[1.115, 1.214]	[1.070, 1.111]	16,687.3

[a] Minimum.

probabilities were not found statistically significant at either the inland locations conditional on the BHI or the coastal locations conditional on the NOI.

For the borrowing strength approach, the BIC values are included in Table XII for the daily precipitation occurrence transition probabilities at the four inland locations conditional on the BHI. The best model involves varying both of the transition probabilities, P_{01} and P_{11}, conditional on the BHI, but constraining their effect to be same at each location (i.e., borrowing strength in both cases). The second-best model involves borrowing strength for P_{01}, but with P_{11} not depending on the BHI. It is noteworthy that the alternative model in which both transition probabilities at all four locations vary with the BHI, but the borrowing strength constraint is not imposed (i.e., consistent with a single-site approach), is inferior to no conditioning on the BHI. The same ordering of BIC values is obtained for the precipitation occurrence transition probabilities at the four coastal locations conditional on the NOI (not shown).

These effects on the transition probabilities (e.g., Δ_{01} is estimated as about 1.17 and Δ_{11} as 1.09 for the inland locations conditional on BHI; 0.89 and 0.92, respectively, for the coastal locations conditional on NOI) can be converted via (4) into the corresponding effects on the probability of occurrence and persistence parameter. In this case, they correspond primarily to shifts in π (smoothed versions of the unconstrained estimates listed in Tables X and XI, not d). An analogous borrowing strength approach could be applied to precipitation intensity, but the effects of BHI and NOI are too small to attain statistical significance.

6. Aggregative Properties of Stochastic Weather Models

An AR(1) model, as in (1), can be used to generate daily time series of minimum or maximum temperature and these daily values then aggregated to seasonal means. For this reason, the aggregative properties of such models are of interest. The daily mean parameter in (1) is equivalent to the seasonal mean. However, the variance of the seasonal mean temperature depends not only on the daily variance, but also on the first-order autocorrelation coefficient (e.g., chapter 17 in von Storch and Zwiers, 1999). The shift in the mean of daily minimum and maximum temperature, but not necessarily in the variance or autocorrelation, with the BHI (Tables VII and VIII) is consistent with the corresponding result that only the median (or mean) of seasonal mean temperatures is apparently related to the BHI (Figures 2–5).

Likewise, the aggregative properties of stochastic models for time series of daily precipitation amount are of interest. It is convenient to assume a 'chain-dependent process' as a stochastic model for daily precipitation amount, a model that includes two components: (i) a first-order Markov chain model for occurrence as in (3); and (ii) intensities that are independent and identically distributed (Katz and Parlange, 1993; Stern and Coe, 1984). The mean of seasonal total precipitation is directly proportional to both the probability of occurrence of precipitation and the mean intensity (see Appendix C). Yet the seasonal variance is not only directly proportional to the intensity variance, but also nonlinearly related to the probability of precipitation, the persistence parameter of the Markov chain, and the mean intensity (see Appendix C). In particular, an increase in just the probability of a wet day with the BHI or NOI (i.e., as supported by the results in Tables X and XI) will produce an increase in both the mean and variance of seasonal total precipitation as in Figures 6 and 7 (Katz, 1993).

Previous studies of the aggregative properties of stochastic weather models have primarily focused on the tendency for daily stochastic models to underestimate the variance of monthly or seasonal total precipitation (e.g., Mavromatis and Hansen, 2001). This underestimation has sometimes been attributed to the neglect of low frequency sources of variability (Hansen and Mavromatis, 2001), with one proposed remedy being to condition on large-scale circulation measures (Katz and Parlange, 1993, 1996).

Table XIII lists the seasonal standard deviation of winter total precipitation at the four inland locations in the Southeast, as 'induced' by a chain-dependent process for daily precipitation amount with different degrees of conditioning on the BHI. This conditioning includes: (i) no dependence of parameters (denoted by 'none' in the table); (ii) only the transition probabilities of the Markov chain model for occurrence vary according to the constraint (5) (denoted by 'borrow'); and (iii) unconstrained variation of the transition probabilities, as well as of the intensity mean and variance (denoted by 'full'). Appendix C sketches how these induced standard deviations can be obtained (also see Katz and Parlange, 1993, 1996). Unlike the situation in some other regions (e.g., U.S. West Coast in winter; Katz and Parlange, 1993), the chain-dependent process with no conditioning does not underestimate the observed standard deviation (also listed in the table) by very much, except perhaps at Nashville. Moreover, neither type of conditioning increases the standard deviation much relative to that for no conditioning. This behavior is attributable to the relatively weak effect of the BHI on precipitation in

Table XIII

Standard deviation (mm) of winter total precipitation at four inland locations, as induced by conditional stochastic models for daily precipitation given BHI

Site	Conditioning			Observed
	None	Borrow	Full	
ATL	99.5	103.1	109.2	103.9
BIR	108.7	112.3	111.3	111.9
MEM	109.5	112.7	117.2	115.7
NAS	87.9	90.9	96.0	103.1

Table XIV

Spatial correlation of winter total precipitation between pairs of the four inland locations, as induced by conditional stochastic models for daily precipitation given BHI (observed correlation in parentheses)

Site	ATL		BIR		MEM	
BIR	0.09	(0.74)	–	–	–	–
MEM	0.15	(0.28)	0.07	(0.35)	–	–
NAS	0.15	(0.32)	0.07	(0.43)	0.12	(0.77)

the Southeast, perhaps reflecting a more general lack of evidence of any substantial source of low frequency variation.

The spatial correlations between winter total precipitation at the inland locations, as induced by the stochastic models for daily precipitation, can also be examined. An explanation of how to obtain these induced spatial correlations is provided in Appendix C (also see Katz, 2002). Table XIV lists the induced spatial correlations for pairs of the four inland locations in the case of full conditioning (i.e., not imposing the constraints of the borrowing strength approach) of the parameters of the chain-dependent process on the BHI state, along with the observed correlation values. Despite the relatively weak connection with the BH, this approach does produce some positive spatial correlations, but the values are much smaller than those observed. These results cast some doubts on the assumption of conditional spatial independence of precipitation occurrence given the BHI state, made in conjunction with the borrowing strength approach (Section 5).

7. Discussion

This paper deals with the development of a statistical methodology to model time series of daily weather at individual locations conditional on patterns in large-scale atmosphere–ocean circulation. Exploiting the stability of the relationship between circulation and a daily weather statistic across a region, the methodology includes a multi-site approach based on the statistical technique of borrowing strength. The approach is applied to model daily time series of daily minimum and maximum temperature and precipitation amount at locations in the Southeastern U.S. conditional on indices of the Bermuda High. It is established that in winter the daily mean minimum and maximum temperature and probability of precipitation occurrence all tend to be higher when the position of the Bermuda High is farther east than average. No relationship with other daily weather statistics, such as the minimum or maximum temperature variance or the median precipitation intensity, is identified.

Such results may appear disappointing, perhaps even in conflict with previously published results on the relationship between circulation indices and spatially and temporally aggregated climate data. Yet they most likely reflect the difficulties that arise in disaggregation (or downscaling), particularly for variables like precipitation. In particular, determining the extent to which a correlation with seasonal total precipitation corresponds to effects on storm frequency or intensity is a challenging statistical problem.

The methodological approach presented here could be extended in several respects. In the borrowing strength technique, the assumption of conditional spatial independence for precipitation occurrence could be relaxed and spatial dependence explicitly modeled. Rather than restricting attention to indices that assume only a small number of states, it would be straightforward to condition on a continuous index (Woolhiser et al., 1993). Finally, an alternative approach that should result in much stronger relationships involves conditioning on high, instead of low, frequency information about circulation (i.e., smaller-scale circulation indices that vary on a daily time scale) (Bellone et al., 2000; Tebaldi, 2000).

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Appendix A: Model Fitting for Daily Temperature

The stochastic model for time series of daily temperature (1) can be reexpressed as:

$$X_t = \beta_0 + \beta_1 X_{t-1} + \beta_2 i + \beta_3 i X_{t-1} + \epsilon_t(i), \ \ \mathrm{var}[\epsilon_t(i)] = \sigma_\epsilon^2(i). \tag{A1}$$

Here β_0, β_1, β_2, and β_3 are regression parameters, $\sigma_\varepsilon(i)$ the standard deviation of the error term (i.e., equivalent to $\sigma_a(i)$ in (1)), and i the circulation index state (i.e., 0 or 1). Models (i)–(iv) listed in Section 4.1 can all be fitted by multiple regression analysis, imposing constraints in (A1): (i) $\beta_2 = \beta_3 = 0$, $\sigma_\varepsilon(0) = \sigma_\varepsilon(1)$; (ii) $\beta_3 = 0$, $\sigma_\varepsilon(0) = \sigma_\varepsilon(1)$; (iii) $\beta_3 = 0$; and (iv) no constraints.

For a regression model of the form (A1), the BIC selects the model for which the following quantity is a minimum (e.g., Chapter 6 in Venables and Ripley, 1999):

$$\mathrm{BIC}(p) = n_0 \ln s_\epsilon^2(0) + n_1 \ln s_\epsilon^2(1) + p \ln m. \tag{A2}$$

Here $s_\varepsilon(i)$ denotes the root mean square error for the fitted model on the subset of the data for which the index $= i$ (consisting of a total of n_i days). The first two terms on the right-hand side of (A2) constitute the goodness-of-fit component, whereas the last term is a penalty for the number of parameters p estimated and depends on the sample size of m years as well (for a discussion of how to choose the appropriate sample size, see Kass and Wasserman, 1995).

Appendix B: Borrowing Strength for Daily Precipitation Occurrence

Let $n_{jk}(i, s)$ denote the ‘transition count’ (i.e., number of times precipitation occurrence state j is followed by state k) given circulation index state i at site s. The common effect Δ_{jk} is estimated from $n_{jk}(i, s)$ by

$$\hat{\Delta}_{jk} = [n_{jk}(1,\cdot)/n_{j\cdot}(1,\cdot)]/[n_{jk}(0,\cdot)/n_{j\cdot}(0,\cdot)]. \tag{B1}$$

Here $n_{jk}(i,\cdot) = \Sigma_s n_{jk}(i, s)$, $n_{j\cdot}(i,\cdot) = \Sigma_s n_{j\cdot}(i, s)$ and $n_{j\cdot}(i, s) = n_{j0}(i, s) + n_{j1}(i, s)$.

Then $P_{jk}(i, s)$ can be obtained from Δ_{jk} and $P_{jk}(s)$ (i.e., the transition probability without conditioning on the index) through the relationship

$$P_{jk}(1, s) = [\Delta_{jk} P_{jk}(s)]/[1 - w_j(s) + \Delta_{jk} w_j(s)] \tag{B2}$$

and (5). Here $w_j(s) = [w\ n_{j\cdot}(1, s)]/[(1 - w)n_{j\cdot}(0, s) + w\ n_{j\cdot}(1, s)]$, where w denotes the fraction of years for which the index assumes state 1.

The BIC selects the Markov chain model for which the following quantity is a minimum (e.g., Katz and Parlange, 1993):

$$\mathrm{BIC}(p) = -2\Sigma_{s,i,j,k}\, n_{jk}(i, s) \ln \hat{P}_{jk}(i, s) + p \ln(mS). \tag{B3}$$

Here p denotes number of parameters a given model requires be estimated and m the number of years of data at the S sites. In (B3), $\hat{P}_{jk}(i, s)$ is the estimate obtained by first estimating Δ_{jk} through (B1) and then substituting this estimate into (B2) and (5) ($P_{jk}(s)$ in (B2) is estimated by conventional maximum likelihood (e.g., Katz and Parlange, 1993).

Appendix C: Induced Variance and Correlation for Seasonal Total Precipitation

Let S_T denote the daily precipitation amount totaled over T days; that is, $S_T = Z_1 + Z_2 + \cdots + Z_{N(T)}$, where Z_l denotes the precipitation intensity on the lth wet day and $N(T)$ the total number of wet days. The conditional mean and variance of S_T given a circulation index state i can be expressed by (e.g., Katz and Parlange, 1993):

$$\begin{aligned} E(S_T \mid i) &= T\pi_i\mu_Z(i), \\ \mathrm{var}(S_T \mid i) &\approx T\{\pi_i\sigma_Z^2(i) + \pi_i(1-\pi_i)[(1+d_i)]/(1-d_i)]\mu_Z^2(i)\}, \\ &\quad \text{for large } T. \end{aligned} \tag{C1}$$

Here $\mu_Z(i)$ and $\sigma_Z^2(i)$ denote the mean and variance of daily intensity given index state i.

The unconditional (or 'induced') variance is related to the conditional means and variances (C1) by (Katz and Parlange, 1996):

$$\begin{aligned} \mathrm{var}(S_T) = {} & (1-w)\mathrm{var}(S_T \mid 0) + w\,\mathrm{var}(S_T \mid 1) \\ & + w(1-w)[E(S_T \mid 1) - E(S_T \mid 0)]^2. \end{aligned} \tag{C2}$$

Let the total precipitation at two sites be denoted by S_T and S'_T, respectively. Under the assumption that S_T and S'_T are conditionally independent given the index, the induced correlation between S_T and S'_T is related to the conditional means and variances (C1) by (Katz, 2002):

$$\begin{aligned} \mathrm{corr}(S_T, S'_T) = {} & \{w(1-w)[E(S_T \mid 1) - E(S_T \mid 0)][E(S'_T \mid 1) \\ & - E(S'_T \mid 0)]\}/[\mathrm{var}(S_T)\mathrm{var}(S'_T)]^{1/2}. \end{aligned} \tag{C3}$$

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