Generation of Simulated Daily Precipitation and Air and Soil Temperatures

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Abstract

This paper describes a maximum likelihood method using historical weather data to estimate a parametric model of daily precipitation and maximum and minimum air temperatures. Parameter estimates are reported for Brookings, SD, and Boone, IA, to illustrate the procedure. The use of this parametric model to generate stochastic time series of daily weather is then summarized. A soil temperature model is described that determines daily average, maximum, and minimum soil temperatures based on air temperatures and precipitation, following a lagged process due to soil heat storage and other factors.

Key words: Air temperatures, maximum soil temperatures, minimum soil temperatures, parametric model, precipitation, soil heat storage, stochastic time series.

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Introduction

Time series of daily weather variables such as precipitation and maximum and minimum air temperatures are used in many applications. Examples include soil temperature models (Logan et al. 1979, Gupta et al. 1981), models of arthropod or plant development (Naranjo and Sawyer 1989, Kiniry et al. 1992), and watershed hydrology models for flood control assessments (Matalas 1967). Historical data can be used for deterministic versions of these models, but if the analysis requires longer time series, generated times series that accurately reflect actual weather are needed. To assess uncertainty created by weather events, sampling with or without replacement from historical data has been used for bio-economic analysis (Pannell 1990, Mjelde et al. 1988). Because this method is limited to observed weather, however, it may not capture the full range of weather variability or shifts that have occurred due to climate change. The approach presented here estimates a parametric model of the underlying stochastic processes, then describes the generation of simulated time series that exhibit the same uncertainty as the observed daily weather. The weather model is adapted from Richardson (1981), whose model serves as the basis for WGEN, the weather generation model used by EPIC¾the Erosion-Productivity Impact Calculator (Richardson and Wright 1984, Williams 1995). The soil temperature model is a modification of Potter and Williams (1994) which is also used by EPIC.

The paper begins with a brief description of the historical daily weather data used to estimate model parameters for Boone, IA, and Brookings, SD. Then the estimation process for the precipitation parametric model is described and parameter estimates are reported; the procedure is repeated for the model of air temperatures. Next, an algorithm to generate simulated time series of the weather variables using the parametric model is summarized. Lastly, a model that determines soil temperatures as functions of air temperatures and precipitation is described.

Historical Weather Data

The National Climatic Data Center's (NCDC) Validated Historical Daily Data was obtained on CD-ROM for hundreds of weather stations throughout the United States (EarthInfo 1996). Using the accompanying software package, all observations of the daily maximum and minimum air temperature and total precipitation for weather stations in Brookings, SD, and Boone, IA, were exported. For Brookings this information included observations from January 1, 1893, to December 31, 1994, (102 years or 37,230 days), with 441 days missing (<1.2 percent). For Boone the observations covered May 1, 1948, to December 31, 1994, (47 years or 16,837 days), with 228 days missing (< 1.35 percent). These data were used to estimate all parameters for stochastic temperature and precipitation generation. In leap years, data for February 29 were deleted so that every year had 365 days. The error introduced by this deletion occurred during a period generally unimportant to crop production in the Midwest. The econometrics software package Time Series Program (TSP) 4.3 (TSP International 1995) was used to estimate all parameters. The TSP defaults for missing data points were used.

Precipitation Model Parameter Estimation

Markov Model of Daily Precipitation Status

Following Richardson (1981), assume a first-order Markov chain model with two states that generates the observed series of wet and dry days. A first-order Markov chain is defined by its transition matrix, which contains the probabilities that the process transitions from one state to the next, conditional on the current state. Typically, rows represent current states and columns represent future states for a transition matrix (Lial et al. 1998). A transition matrix must be square, because all possible states of the process must be used as both rows and columns. Furthermore, each row sums to one because the process must end in one of the states specified by the process.

For the process modeled here there are two states: a day is either wet or dry. The probability that a day is wet or dry is conditional on whether the previous day was wet or dry. This is summarized in the transition matrix P: $P = \begin{bmatrix} P_{dd} & P_{dw} \\ P_{wd} & P_{ww} \end{bmatrix} = \begin{bmatrix} P_{dd} & 1 - P_{dd} \\ P_{wd} & 1 - P_{wd} \end{bmatrix}$, where P_{dd} is the probability of a dry day following a dry day and P_{wd} is the probability of a dry day following a wet day, using the convention that row subscripts define current states and column subscripts define future states. Thus, the precipitation status for any given day is completely defined by the two parameters P_{dd} and P_{wd}; however, a total of 730 parameters must be estimated, because parameter values are specific to each day and there are 365 days in a year.

To reduce the number of parameters, the seasonal periodicity exhibited by the transition probabilities is utilized. Following the maximum likelihood method described by Woolhiser and Pegram (1979), a Fourier series is estimated for each transition probability. First the number of observed transitions from each state on each day of the year is calculated and denoted a_{ij}^{n}, where *iÎ{d,w}* and indexes current states, *jÎ{d,w}* and indexes future states, and n denotes the day of the year. The log-likelihood function is:

$$\ln L(\phi \mid X) = \sum_{n=1}^{365} \begin{bmatrix} a_{dd}^{n} \ln\left(P_{dd}(n)\right) + a_{dw}^{n} \ln\left(1 - P_{dd}(n)\right) + \\ a_{wd}^{n} \ln\left(P_{wd}(n)\right) + a_{ww}^{n} \ln\left(1 - P_{wd}(n)\right) \end{bmatrix}, \tag{1}$$

$$P_{dd}(n) = A_d + \sum_{k=1}^{H_d} \left[C_{dk} \cos\left(\frac{nk}{K}\right) + S_{dk} \sin\left(\frac{nk}{K}\right) \right], \tag{2}$$

$$P_{wd}(n) = A_w + \sum_{k=1}^{H_w} \left[C_{wk} \cos\left(\frac{nk}{K}\right) + S_{wk} \sin\left(\frac{nk}{K}\right) \right], \tag{3}$$

where K = 365/2p » 58.091554 is the necessary normalizing constant; H_d and H_w are the number of harmonics estimated for $P_{dd,}$ and $P_{wd,}$ respectively; f is the parameter vector of Fourier coefficients $\{A_d, A_w, C_{dk_d}, S_{dk_d}, C_{wk_w}, S_{wk_w}\}$; and X is the matrix of the a_{ij}^{n}, the number of observed transitions. The number of harmonics for each Fourier series is increased one at a time until the addition of a harmonic fails a Likelihood Ratio test at the 5 percent level of significance. The maximum likelihood estimates and standard errors are reported in Table 1 for Brookings and Boone; Figures 1 and 2 illustrate the fit and smoothing of the data provided by the Fourier series.

Exponential Model of Daily Precipitation

Several alternatives are available for a stochastic model of the amount of precipitation on wet days, but Richardson's exponential model was chosen for its simplicity. Define R_n as the amount of precipitation on a given day n when n is a wet day. Assume R_n is distributed according to the exponential distribution with probability density function $f(R_n) = \lambda_n e^{-\lambda_n R_n}$, where l_n is specific to each day. As with the transition probabilities, the seasonal periodicity exhibited by the l_n is used to reduce the number of required parameters.

Following the maximum likelihood method described by Woolhiser and Pegram (1979), a Fourier series is estimated for the parameter l. To express the log-likelihood function, define R_{ny} as the observed amount of precipitation for day n in year y, and define

$D_{ny} = \begin{cases} 0 & \text{if } R_{ny} = 0 \\ 1 & \text{if } R_{ny} > 0 \end{cases}$. Then the log-likelihood function is:

$$\ln L(\theta \mid R, D) = \sum_{n=1}^{365} \sum_{y=1}^{T} D_{ny} \left[\ln(\lambda(n)) - \lambda(n) R_{ny} \right], \tag{4}$$

$$\lambda(n) = A + \sum_{k=1}^{H} \left[C_k \cos\left(\frac{nk}{K}\right) + S_k \sin\left(\frac{nk}{K}\right) \right], \tag{5}$$

where *q* is the parameter vector of Fourier coefficients $\{A, C_k, S_k\}$, T is the number of years, and H is the number of harmonics. For estimation, the number of harmonics is increased one at a time until the addition of a harmonic fails a Likelihood Ratio test at the 5 percent level of significance. The maximum likelihood estimates and standard errors are reported in Table 2 for Brookings and Boone; Figure 3 illustrates the fit and smoothing of the data provided by the Fourier series.

Air Temperature Model Parameter Estimation

Daily Mean and Standard Deviation of Maximum and Minimum Air Temperatures

Following the procedure described by Richardson (1981) and Matalas (1967), assume that daily maximum and minimum air temperatures are a continuous, multivariate, weakly stationary process with daily means and standard deviations conditional on the wet or dry state of the day. For each day of the year, calculate the mean and standard deviation of the maximum and minimum air temperatures separately for wet and dry days. This calculation yields eight parameter estimates for each day of the year: the wet and dry mean and the wet and dry standard deviation for the maximum temperature, and the same four for the minimum temperature. Again utilize seasonal periodicity to reduce this set of parameters by using a least squares criterion to estimate eight separate Fourier series. The general equation used for each series is:

$$\theta(n) = A + \sum_{k=1}^{H}\left[C_k \cos\left(\frac{nk}{K}\right) + S_k \sin\left(\frac{nk}{K}\right)\right], \tag{6}$$

where q is the parameter for which the Fourier series is being estimated and n is the day of the year. The estimated coefficients are A, the C_k and S_k, and H, the number of harmonics for the series. For each Fourier series, harmonics are increased one at a time until the addition of a harmonic fails a Likelihood Ratio test at the 5 percent level of significance. Coefficient estimates and standard errors for all eight Fourier series for both Brookings and Boone are reported in Tables 3–10; Figures 4–11 illustrate the fit provided by the Fourier series for both locations.

Maximum and Minimum Air Temperature Residuals

Following the method described by Matalas (1967), calculate the maximum and minimum temperature residuals for each observation by subtracting the appropriate wet or dry mean observed on that day of the year (not estimated by the Fourier series) and dividing by the appropriate wet or dry standard deviation observed on that day of the year. The temperature residuals for any day of the year are the deviation of observed temperatures from the appropriate wet or dry mean, normalized by the appropriate wet or dry standard deviation. Next assume that the maximum and minimum air temperature residuals follow a multivariate weakly stationary process defined by:

$$\chi_{n+1,y} = A\chi_{n,y} + B\varepsilon_{n+1,y} \tag{7}$$

where $e_{n,y}$ is a (2 x 1) matrix of independently distributed standard normal (mean zero, variance one) random variables for the specified day and year, and $c_{n,y}$ and $c_{n+1,y}$ are (2 x 1) matrices of the maximum and minimum air temperature residuals for the specified day and year.

A and B are (2 x 2) matrices whose elements are functions of the lag 0 and lag 1 serial- and cross-correlation coefficients of the observed residuals, defined so that any series of residuals generated by a series of standard normal errors exhibits the same serial- and cross-correlation as the observed residuals. Note (7) implies that the residuals are normally distributed and follow a first-order linear autoregressive process. A and B are determined by the following equations:

$$A = M_1 M_0^{-1} \tag{8}$$

$$BB^T = M_0 - M_1 M_0^{-1} M_1^T \cdot \tag{9}$$

M_0 and M_1 are matrices of the lag 0 and lag 1 correlation coefficients, respectively, defined as follows:

$$M_0 = \begin{bmatrix} 1 & \rho_{X_0 N_0} \\ \rho_{N_0 X_0} & 1 \end{bmatrix} \tag{10}$$

$$M_1 = \begin{bmatrix} \rho_{X_0 X_{-1}} & \rho_{X_0 N_{-1}} \\ \rho_{N_0 X_{-1}} & \rho_{N_0 N_{-1}} \end{bmatrix}, \tag{11}$$

where X and N denote the residuals for the maximum and minimum air temperature, respectively, and their subscripts denote lag 0 or lag 1. Thus $\rho_{X_0 N_0}$ is the lag 0 cross-correlation coefficient between the residuals for the maximum air temperature and the residuals for the minimum air temperature. $\rho_{X_0 X_{-1}}$ and $\rho_{N_0 N_{-1}}$ are the lag 1 serial correlation for the residuals of the maximum and minimum air temperature, respectively. $\rho_{X_0 N_{-1}}$ is the cross-correlation coefficient between the lag 0 maximum air temperature residuals and the lag 1 minimum air temperature residuals, and $\rho_{N_0 X_{-1}}$ is the cross-correlation coefficient between the lag 0 minimum air temperature residuals and the lag 1 maximum air temperature residuals. Table 11 reports the serial-correlation and cross-correlation coefficients needed to construct the M_0 and M_1 matrices for Brookings and Boone.

To solve (9) for B, first define a matrix $Z = BB^T$. Using spectral decomposition, $Z = CLC^T$, where C is the matrix of eigenvectors, and L is the matrix with the associated eigenvalues down the main diagonal and zeros for all other elements [see Greene (1997), p. 38]. Note that $BB^T = Z^{½}Z^{½T} = Z$, implying that $B = Z^{½}$, then by Greene's Theorem 2.10, $B = Z^{½} = CL^{½}C^T$. Table 11 also reports the elements of A and B for both locations.

Generation of Simulated Weather

Extensive time series for precipitation and maximum and minimum air temperatures that exhibit appropriate serial- and cross-correlations can be generated once the parametric model is estimated. Initialize the process by specifying the previous day's maximum and minimum temperature residuals and its precipitation status as either wet or dry. Assuming that the previous day was dry and that both temperature residuals were zero seems reasonable, since a dry day is most likely for the two locations reported here and residuals of zero imply that maximum and minimum temperatures were exactly at their respective means. Also, substitute all estimated parameter values into the appropriate Fourier series.

In general, the algorithm proceeds by first determining the precipitation status of the current day conditional on the previous day's precipitation status, then determining the daily maximum and minimum temperatures conditional on the current day's precipitation status and the previous day's temperatures. The specifics of the algorithm are outlined in a series of steps for a given day n:

1. Calculate the probability that day n is dry by using Equation (2) if day $n - 1$ was dry or Equation (3) if day $n - 1$ was wet.

2. Draw a uniform random variable between zero and one; if it exceeds the probability that day n is dry, then day n is wet, else day n is dry.

3. If day n is dry, go to the next step, else use Equation (5) to calculate l and draw the precipitation amount as an exponential random variable with mean $1/l$.

4. Draw two independent standard normal random variables to construct the e matrix, then use Equation (7) to calculate the maximum and minimum air temperature residuals.

5. Calculate the mean and standard deviation of the maximum and minimum air temperatures using the appropriate forms of Equation (6) depending on the precipitation status of day n.

6. Calculate day n's maximum and minimum air temperature by multiplying each residual by the appropriate standard deviation and adding the appropriate mean.

The generation of reliable random numbers using computers is an essential part of generating simulated weather data but is not a simple process. Press et al. (1992) expressly warn researchers against using random numbers supplied by software systems, because the series of numbers may quickly repeat itself. Repetition of random series is a real concern if rather long time series are needed, as can be the case for Monte Carlo analysis. Press et al. (1992) describe several algorithms for generating uniform random variables (e.g., L'Ecuyer's long-period generator with a Bays-Durham shuffle) and transformation techniques for obtaining random variables from other distributions from uniform random variables.

Soil Temperature Model

Soil temperatures in the top soil layer are important in crop production. Soil temperatures determine the germination and growth of planted crops and weeds, as well as regulate the metabolic activity and development of soil microbes, nematodes, fungi, worms, and insects. This section presents a model of soil temperatures in the top 10-cm layer. The method of Potter and Williams (1994) is used with a few modifications to determine the daily average soil temperature as a function of air temperature. The method of Logan et al. (1979) is modified in accordance with data presented in Gupta et al. (1983) to determine the daily maximum and minimum soil temperatures as functions of the average soil temperature.

Average Soil Temperature

The model of Potter and Williams (1994) derives the average soil temperature for a layer below the surface by first modeling the temperature of the bare soil surface, which closely follows the air temperatures, then adjusting this bare soil surface temperature to account for soil cover. Next, a physically derived depth-weighting factor (*DWF*) is used to determine the average soil temperature at any given depth between the soil surface and the constant temperature depth. Following their model, $PTBS_n$, the potential temperature of the bare soil for day *n*, depends on a day’s precipitation status as follows:

$$PTBS_n = \begin{cases} T_{Min,n} + \dfrac{NWD_n}{30}\alpha_{\mathrm{n}}^{\mathrm{air}} & \text{if the day is wet} \\ T_{Avg,n} + \dfrac{NWD_n}{30}\alpha_{\mathrm{n}}^{\mathrm{air}} & \text{if the day is dry,} \end{cases} \tag{12}$$

where *NWD* is the number of wet days over the past thirty days (including the current day); $T_{Max,n}$, $T_{Min,n}$, and $T_{Avg,n}$ are the maximum, minimum, and average air temperatures for day *n* (the average temperature is the simple average of the maximum and minimum); and $\alpha_n^{air} = \frac{1}{2}\left(T_{Max,n}^{air} - T_{Min,n}^{air}\right)$ is the amplitude of the temperature change on day *n*. The actual temperature of the bare soil (TBS_n) is then the two-day moving average of the *PTBS*.

Next, the average soil surface temperature for day *n* ($T_{Avg,n}^{surface}$) uses the *TBS*, but accounts for soil cover by using a lagged cover factor (LCF_n) as follows:

$$T_{Avg,n}^{surface} = LCF_n TBS_{n-1} + (1 - LCF_n)TBS_n \tag{13}$$

$$LCF_n = MAX\{BCF_n, SCF_n\}. \tag{14}$$

BCF_n is the biomass cover factor and SCF_n is the snow cover factor for day *n* calculated by the following empirically derived equations:

$$BCF_n = \frac{B_n}{B_n + \exp(5.3396 - 2.3951 B_n)} \tag{15}$$

$$SCF_n = \frac{S_n}{S_n + \exp(2.303 - 0.2197 S_n)}, \tag{16}$$

where B_n is the total above ground crop biomass and surface residue (Mg/ha) and S_n is the water content of the snow cover (mm) on day *n*. After validating the model with data from three locations, Potter and Williams impose the following restrictions:
0 £ BCF_n £ 0.19 and 0 £ SCF_n £ 0.95.

To determine B_n, the base cover contributed by crop residue is assumed to be 1.4 Mg/ha, which is approximately the amount of residue left from continuous corn production under conventional tillage. This is calculated by assuming a 1:1 ratio of grain to residue production for corn, following Larson et al. (1978, cited in Havlin et al. 1990) and assuming a bushel of corn weighs 56 lbs. (USDA 1979). Thus a typical yield for Brookings of 100 bu/ac implies 6.3 Mg/ha of residue and a typical yield for Boone of 150 bu/ac implies 9.4 Mg/ha. Standard tillage operations for conventional tillage corn are from state extension budgets for South Dakota (chisel plow and tandem disk) and Iowa (chisel plow, tandem disk, and field cultivator) (SDSU Extension Economics 1998, ISU Extension 1998). Residue mixing efficiencies typical for these operations are from the EPIC User's Guide: chisel plow, 0.42; tandem disk, 0.50; field cultivator, 0.70 (Mitchell et al. 1997). Then, 6.3 x 0.42 x 0.50 = 1.32 and 9.4 x 0.42 x 0.50 x 0.70 = 1.38 are rounded up to 1.4 to serve as a simple estimate of the base cover from crop residue.

To include the contribution of growing crop biomass to B_n, the year is divided into four periods roughly coinciding with seasons: (1) no living crop biomass, (2) linear biomass accumulation during crop growth, (3) maintenance of living crop biomass during summer, and (4) linear decline of crop biomass during senescence and harvest. For each of these periods, the value of B_n is determined as follows:

November 1 to plant day $\qquad B_n = 1.4 \qquad$ (17a)

Plant day to peak flower $$B_n = 1.4 + 7\left(\frac{\text{current day} - \text{plant day}}{\text{peak flower} - \text{plant day}}\right) \tag{17b}$$

Peak flower to harvest $$B_n = 9.4 \tag{17c}$$

Harvest to November 1 $$B_n = 9.4 - 7\left(\frac{\text{current day} - \text{harvest}}{305 - \text{harvest}}\right). \tag{17d}$$

Plant days range from early May to early June, with early to mid-May typical. Peak flower depends on the maturity of the corn hybrid and occurs from early August to mid-September, with mid- to late August typical. Harvest can range from as early as late September to as late as late November, but mid-October is typical.

To determine S_n, the water content of snow cover (mm), a model of snowfall accumulation and snowmelt is used. If precipitation occurs on a day, it is categorized as snowfall if the maximum air temperature is less than 40° F and the average is below 35° F. The multiple-layer soil temperature model of snowmelt developed by Williams (1995) is adapted to the single-layer soil temperature model used here. If a snow pack is present and the average soil temperature on day n ($T_{Avg,n}^{soil}$) is above zero, then the millimeters of snowmelt on day n (SM_n) occurs according to the empirically derived equation:

$$SM_n = T_{Avg,n}\left(1.52 + 0.54 MIN\left\{T_{Avg,n}^{soil}, T_{Avg,n}\right\}\right). \tag{18}$$

The method of Potter and Williams (1994) is then used to determine the daily average soil temperature at 5 cm, the middle of the top 10 cm of soil, as follows:

$$T_{Avg,n}^{soil} = 0.5T_{Avg,n-1}^{soil} + 0.5T_{Avg,n}^{surface} + 0.5DWF\left(\overline{T} - T_{Avg,n}^{surface}\right). \tag{19}$$

$\overline{T}$ is the long-term average air temperature that approximates the constant soil temperature maintained at some sufficient depth (6.2°C for Brookings and 8.5°C for Boone) and DWF is the depth-weighting factor. Potter and Williams's Equations (7) – (11) were used to determine the value of DWF over a wide range of soil bulk density and soil water conditions. The value changes very little (0.2237 - 0.2260), even under extraordinarily unlikely conditions, so an average value of 0.225 is used for all simulations. Because Potter and Williams note that the model tends to underpredict average soil temperatures, the average is increased by 2.5 percent.

Maximum and Minimum Soil Temperatures

To determine the daily maximum and minimum soil temperatures, the method of Logan et al. (1979) is modified to extrapolate from air temperature extremes to near-surface soil temperature extremes. Their method was developed to extrapolate from measured temperatures at one depth to temperatures at another depth, not from surface to below-ground temperatures. Essentially, the method assumes that the amplitude at one depth is proportional to the amplitude at another depth, with the constant of proportionality depending on the difference in depth. Using Logan et al.'s Equation (9) gives a value of 0.98 for a depth difference of 10 cm. Assuming that the soil surface temperature is the same as the air temperature, this factor implies that the amplitude of soil temperatures at 5 cm is 98 percent of the amplitude of the air temperature. However, this does not account for dampening due to soil cover, nor due to additional heat input from solar radiation, especially significant in spring when the soil is dark and crops do not shade the soil surface.

To adjust for soil cover, the constant of proportionality is reduced to 0.95 for days between March 1 and November 15 (approximately soil thaw to soil freeze). Benoit and Van Sickle (1991) report data on winter soil temperatures for various tillage-residue management systems in west central Minnesota. These data indicate that the difference between the maximum and minimum air temperatures is around 10–12°C, whereas the difference between the maximum and minimum soil temperatures at 5 cm is about 2–4°C, or about 25 percent less. Thus from November 15 to March 1, the constant of proportionality is set to 0.25.

Research has also shown that the variation of near-surface soil temperatures around the average is asymmetric and changes throughout the season due to tillage and crop growth (Gupta et al. 1981, Gupta et al. 1983, Potter and Williams 1994). Data reported by Gupta et al. (1983) indicate that in spring the maximum soil temperature is approximately 25 percent more above the average soil temperature than the maximum air temperature is above the average air temperature. This occurs because the soil is generally dark and no crops provide shade. In summer, the factor is approximately 15 percent because solar radiation has increased, but crops begin to provide increasingly more shade.

All these adjustments are summarized in the equations used to determine the soil maximum and minimum temperatures:

Spring (March 1 to plant day + 42 days):

$$T^{soil}_{Max,n} = 1.25\left[T^{soil}_{Avg,n} + 0.95\alpha^{air}_{n}\right] \tag{20a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.95\alpha^{air}_{n}\right] \tag{20b}$$

Summer (plant day + 42 days to September 15):

$$T^{soil}_{Max,n} = 1.15\left[T^{soil}_{Avg,n} + 0.95\alpha^{air}_{n}\right] \tag{21a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.95\alpha^{air}_{n}\right] \tag{21b}$$

Fall (September 15 to November 15):

$$T^{soil}_{Max,n} = 1.00\left[T^{soil}_{Avg,n} + 0.95\alpha^{air}_{n}\right] \tag{22a}$$

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.95\alpha^{air}_{n}\right] \tag{22b}$$

Winter (November 15 to March 1):

$$T^{soil}_{Max,n} = 1.00\left[T^{soil}_{Avg,n} + 0.25\alpha^{air}_{n}\right] \tag{23a}$$

.

$$T^{soil}_{Min,n} = 1.00\left[T^{soil}_{Avg,n} - 0.25\alpha^{air}_{n}\right] \tag{23b}$$

The overall performance of the soil temperature model is difficult to evaluate without comparing to actual data. However, the model is based on assumptions and equations well-tested in the literature; e.g., Potter and Williams (1994) is the soil temperature model used for EPIC. The soil temperature model developed here predicts the daily average, maximum, and minimum soil temperature as a function of the daily maximum and minimum air temperature and precipitation status (wet or dry). Furthermore, the model accounts for the impact of crop growth and seasonal changes, including snowfall accumulation.

Conclusion

This paper describes the estimation of a parametric model of daily precipitation and maximum and minimum air temperatures and the use of that model to generate simulated time series of weather variables. Maximum likelihood equations for estimating the parametric model using historical data are provided and parameter estimates for Brookings, SD, and Boone, IA, are reported. Alternative specifications of the parametric model could be explored to improve the modeling of the underlying stochastic processes. For example, for the precipitation model, higher-order Markov chains or multiple rainfall states could be explored, as well as more flexible distributions such as the gamma or beta for the amount of rainfall on wet days (Richardson 1981). For the daily temperature model, corrections for skewness and kurtosis could be incorporated, or nonnormal error specifications could be used (Matalas 1967). The soil temperature model could be validated by comparing model predictions with actual soil temperature data in a manner similar to that of Potter and Williams (1994).

Table 1. Fourier series coefficient estimates for the probability of a dry day following a dry day and the probability of a wet day following a dry day in Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A_d	0.7807	0.0025	0.7715	0.0037
C_{d1}	0.1031	0.0035	0.0635	0.0051
S_{d1}	-0.0094	0.0035	-0.0206	0.0053
C_{d2}	-0.0015	0.0034		
S_{d2}	0.0183	0.0036		
C_{d3}	-0.0063	0.0034		
S_{d3}	-0.0128	0.0035		
A_w	0.7712	0.0048	0.5716	0.0076
C_{w1}	0.0967	0.0071	0.0492	0.0107
S_{w1}	-0.0063	0.0064	-0.0033	0.0108
C_{w2}	-0.0034	0.0070	0.0384	0.0104
S_{w2}	0.0153	0.0065	0.0499	0.0110
C_{w3}	-0.0067	0.0068	0.0022	0.0107
S_{w3}	-0.0236	0.0067	-0.0248	0.0106

[a] See Equations (2) and (3) for coefficient definitions.
[b] Computed according to the method of Berndt et al. (1974).

Table 2. Fourier series coefficient estimates for the parameter *l* of the exponential probability density function for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	5.2815	0.0560	3.6183	0.0489
C_1	3.4095	0.0920	1.7404	0.0757
S_1	0.9470	0.0608	0.4353	0.0617
C_2	1.2737	0.0806	0.4926	0.0706
S_2	0.7630	0.0715	0.3211	0.0668
C_3	0.4884	0.0702	0.2207	0.0655
S_3	0.3548	0.0728	0.2046	0.0675
C_4	0.1094	0.0555	0.0404	0.0523
S_4	0.3386	0.0580	0.2009	0.0565

[a] See Equation (5) for coefficient definitions.

[b] Computed according to the method of Berndt et al. (1974).

Table 3. Fourier series coefficient estimates for the mean of the maximum air temperature on a dry day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	56.2517	0.0617	60.4045	0.0939
C_1	-29.5203	0.0872	-28.0091	0.1328
S_1	-9.4464	0.0872	-8.5034	0.1328
C_2	-3.0251	0.0872	-3.0917	0.1328
S_2	-0.6941	0.0872	-1.0609	0.1328
C_3	0.1797	0.0872	-0.2957	0.1328
S_3	-0.2027	0.0872	0.3601	0.1328
C_4	0.3126	0.0872	-0.1516	0.1328
S_4	0.8663	0.0872	0.7117	0.1328

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 4. Fourier series coefficient estimates for the mean of the maximum air temperature on a wet day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	51.9957	0.1353	57.3062	0.1533
C_1	-30.5627	0.1914	-27.7780	0.2168
S_1	-9.3814	0.1914	-9.0578	0.2168
C_2	-2.2156	0.1914	-2.3425	0.2168
S_2	-0.3683	0.1914	-1.0260	0.2168
C_3	-0.0083	0.1914		
S_3	-0.6594	0.1914		

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 5. Fourier series coefficient estimates for the mean of the minimum air temperature on a dry day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	31.2684	0.0552	35.7891	0.0851
C_1	-26.3254	0.0781	-25.4551	0.1204
S_1	-8.3304	0.0781	-7.6758	0.1204
C_2	-1.4249	0.0781	-1.2151	0.1204
S_2	-0.5198	0.0781	-0.6731	0.1204
C_3	-0.5433	0.0781	-0.5060	0.1204
S_3	-1.2559	0.0781	-1.0473	0.1204
C_4	0.1131	0.0781		
S_4	-0.2720	0.0781		
C_5	0.0743	0.0781		
S_5	0.3328	0.0781		
C_6	0.4958	0.0781		
S_6	-0.0171	0.0781		

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 6. Fourier series coefficient estimates for the mean of the minimum air temperature on a wet day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	33.5774	0.1367	38.3504	0.1548
C_1	-27.1519	0.1934	-25.0132	0.2189
S_1	-8.7806	0.1934	-8.0771	0.2189
C_2	-3.0643	0.1934	-2.3501	0.2189
S_2	-1.2747	0.1934	-1.2593	0.2189
C_3	-0.7844	0.1934	-0.9538	0.2189
S_3	-1.2311	0.1934	-0.9808	0.2189

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 7. Fourier series coefficient estimates for the standard deviation of the maximum air temperature on a dry day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	11.1102	0.0395	10.0688	0.0670
C_1	2.8808	0.0559	2.9809	0.0947
S_1	1.2214	0.0559	1.3168	0.0947
C_2	-0.5267	0.0559	-0.6754	0.0947
S_2	-0.2341	0.0559	-0.1711	0.0947
C_3	0.1342	0.0559		
S_3	0.2585	0.0559		
C_4	0.2079	0.0559		
S_4	0.3425	0.0559		
C_5	-0.1920	0.0559		
S_5	0.2608	0.0559		
C_6	-0.2079	0.0559		
S_6	0.0854	0.0559		
C_7	-0.0636	0.0559		
S_7	-0.2245	0.0559		
C_8	-0.0874	0.0559		
S_8	-0.2487	0.0559		

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 8. Fourier series coefficient estimates for the standard deviation of the maximum air temperature on a wet day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	10.2603	0.0944	9.8459	0.1166
C_1	1.8704	0.1335	2.0811	0.1649
S_1	0.8781	0.1335	1.2429	0.1649
C_2	-0.6026	0.1335	-0.9649	0.1649
S_2	-0.5283	0.1335	-0.6009	0.1649
C_3	0.5335	0.1335		
S_3	0.4154	0.1335		

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 9. Fourier series coefficient estimates for the standard deviation of the minimum air temperature on a dry day for Brookings, SD, and Boone, IA

	Brookings, SD		**Boone, IA**	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	10.4959	0.0400	9.5900	0.0616
C_1	3.0695	0.0566	2.8803	0.0872
S_1	0.9792	0.0566	0.8108	0.0872
C_2	0.7013	0.0566	0.5321	0.0872
S_2	1.0220	0.0566	0.4681	0.0872
C_3	0.2662	0.0566	0.3502	0.0872
S_3	0.8091	0.0566	0.7953	0.0872
C_4	-0.1969	0.0566		
S_4	-0.2837	0.0566		
C_5	-0.1496	0.0566		
S_5	-0.3494	0.0566		

[a] See Equation (6) for coefficient definitions.

[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 10. Fourier series coefficient estimates for the standard deviation of the minimum air temperature on a wet day for Brookings, SD, and Boone, IA

	Brookings, SD		Boone, IA	
Coefficient[a]	Estimate	Standard Error[b]	Estimate	Standard Error[b]
A	9.3562	0.0970	8.9704	0.1161
C_1	3.8418	0.1371	4.1114	0.1643
S_1	0.9883	0.1371	0.9426	0.1643
C_2	0.6352	0.1371	0.5169	0.1643
S_2	0.5066	0.1371	0.2418	0.1643
C_3	0.1161	0.1371	0.3764	0.1643
S_3	0.5401	0.1371	0.6857	0.1643
C_4	-0.3181	0.1371		
S_4	-0.3372	0.1371		
C_5	-0.1425	0.1371		
S_5	-0.7686	0.1371		
C_6	0.0023	0.1371		
S_6	-0.4120	0.1371		

[a] See Equation (6) for coefficient definitions.
[b] Computed using the Gauss-Newton method with the quadratic form of the analytic first derivatives [see Greene (1997) p. 139].

Table 11. Correlation coefficients for temperature residuals and derived matrix elements for Brookings, SD, and Boone, IA

	Brookings, SD	Boone, IA
Coefficient or Element	Value for Brookings	Value for Boone
$\rho_{X_0N_0} = \rho_{N_0X_0}$	0.69580	0.69215
$\rho_{X_0X_{-1}}$	0.67244	0.61300
$\rho_{N_0N_{-1}}$	0.61889	0.64883
$\rho_{X_0N_{-1}}$	0.51265	0.51185
$\rho_{N_0X_{-1}}$	0.59365	0.55112
$A_{1,1}$	0.61206	0.49666
$A_{1,2}$	0.08678	0.16809
$A_{2,1}$	0.31603	0.19587
$A_{2,2}$	0.39900	0.51326
$B_{1,1}$	0.7160	0.75178
$B_{1,2} = B_{2,1}$	0.19382	0.21057
$B_{2,2}$	0.72656	0.71742

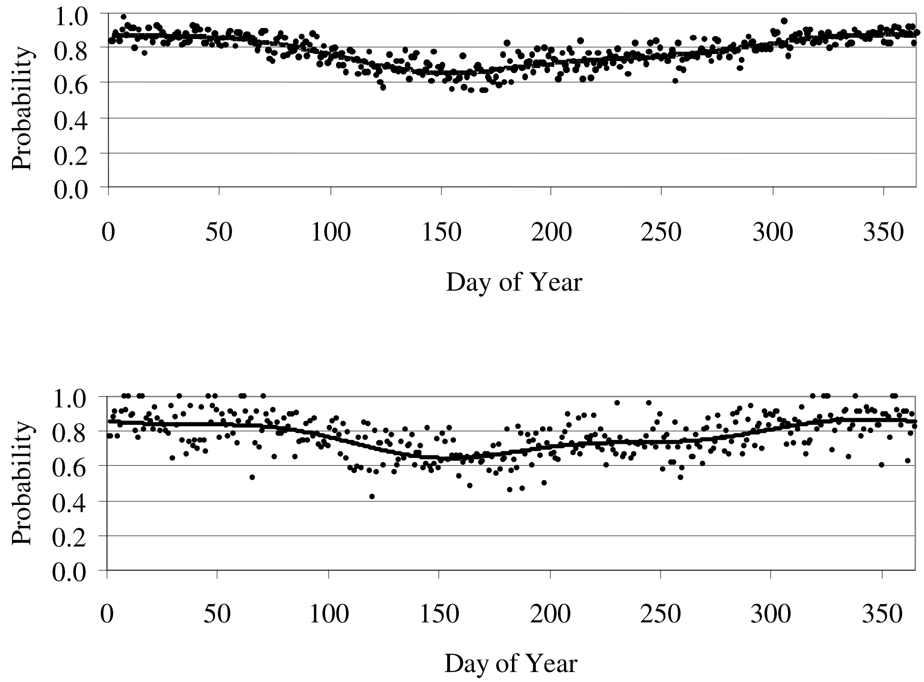

Figure 1. Observed and Fourier series estimated daily probability of a dry day following a dry day (top) and a dry day following a wet day (bottom) in Brookings, SD.

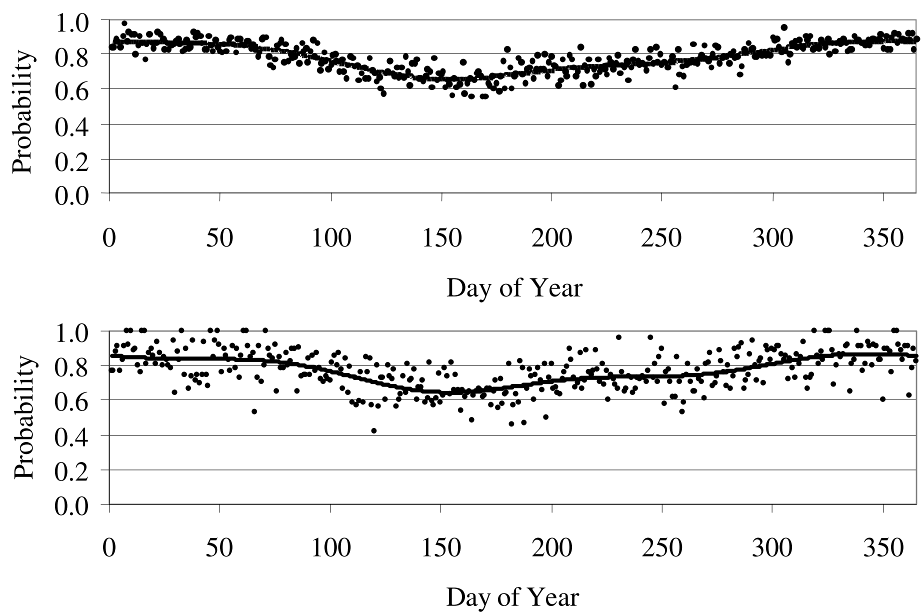

Figure 2. Observed and Fourier series estimated daily probability of a dry day following a dry day (top) and a dry day following a wet day (bottom) in Boone, IA.

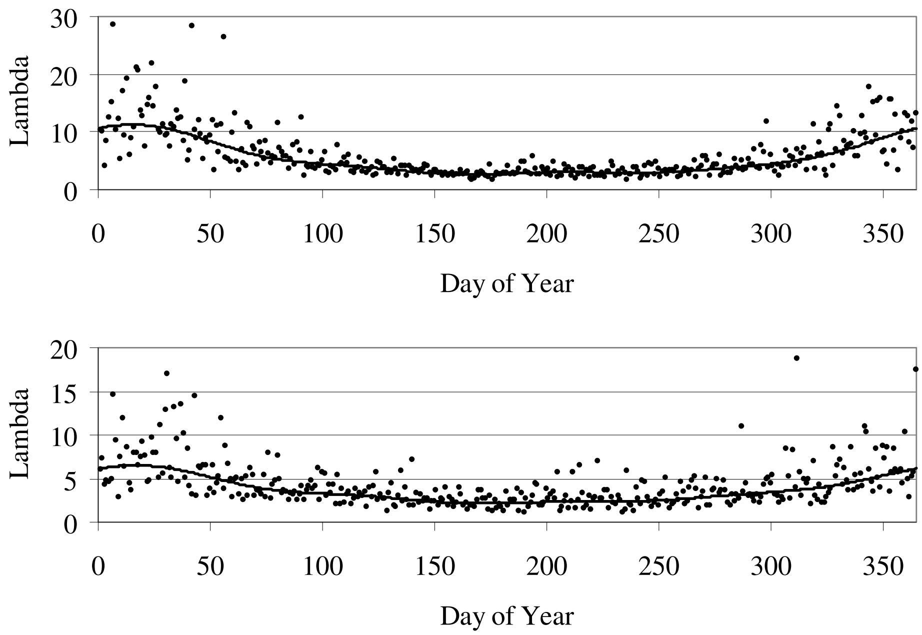

Figure 3. Observed and Fourier series estimated daily value of λ for the exponential probability density function for Brookings, SD, (top) and Boone, IA, (bottom)

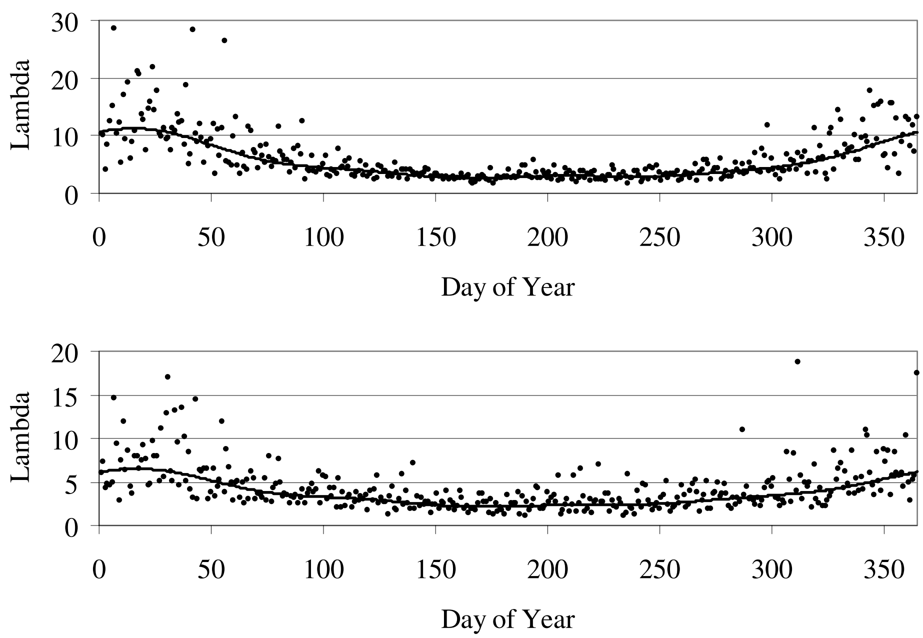

Figure 4. Observed and Fourier series estimated daily mean (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

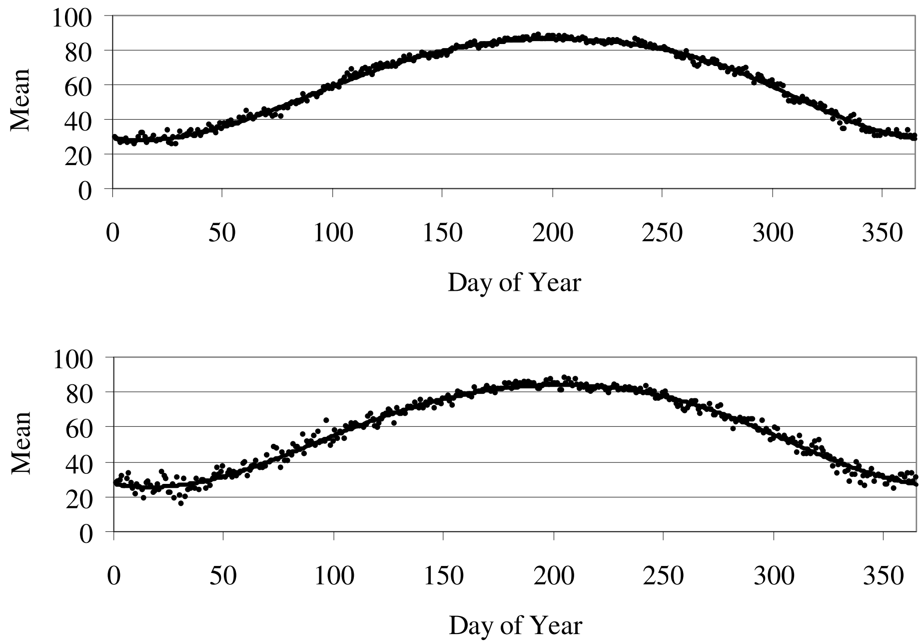

Figure 5. Observed and Fourier series estimated daily mean (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

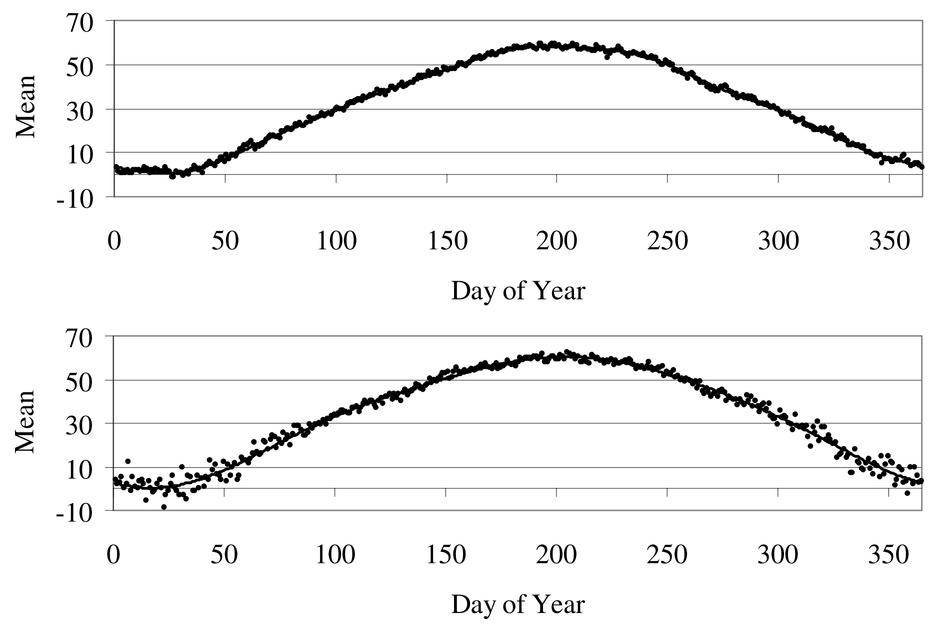

Figure 6. Observed and Fourier series estimated daily mean (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

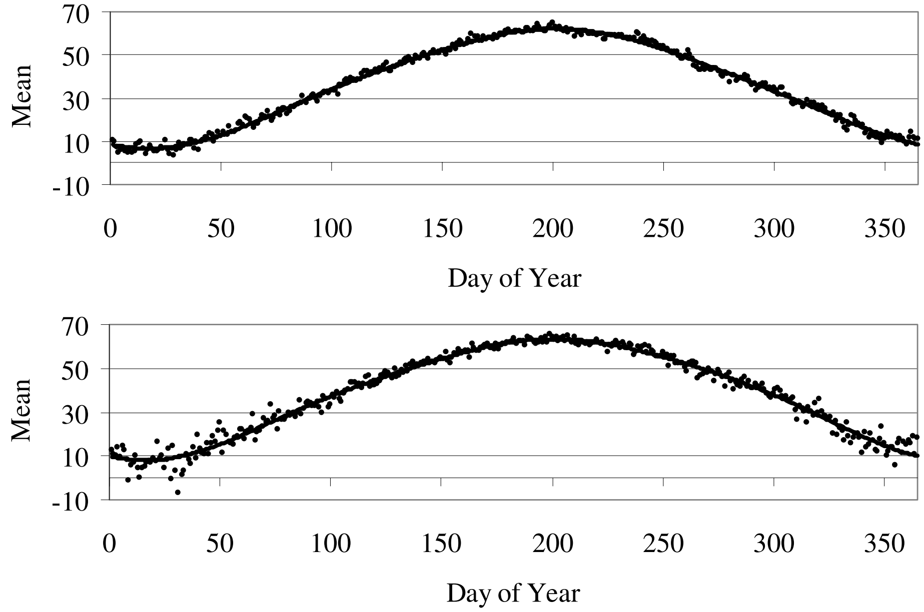

Figure 7. Observed and Fourier series estimated daily mean (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

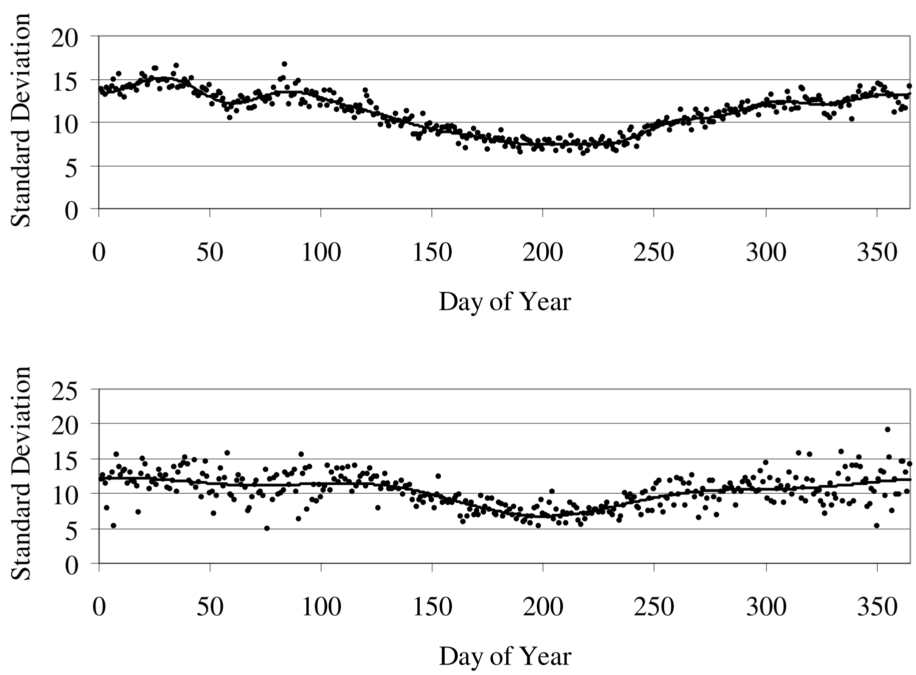

Figure 8. Observed and Fourier series estimated daily standard deviation (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

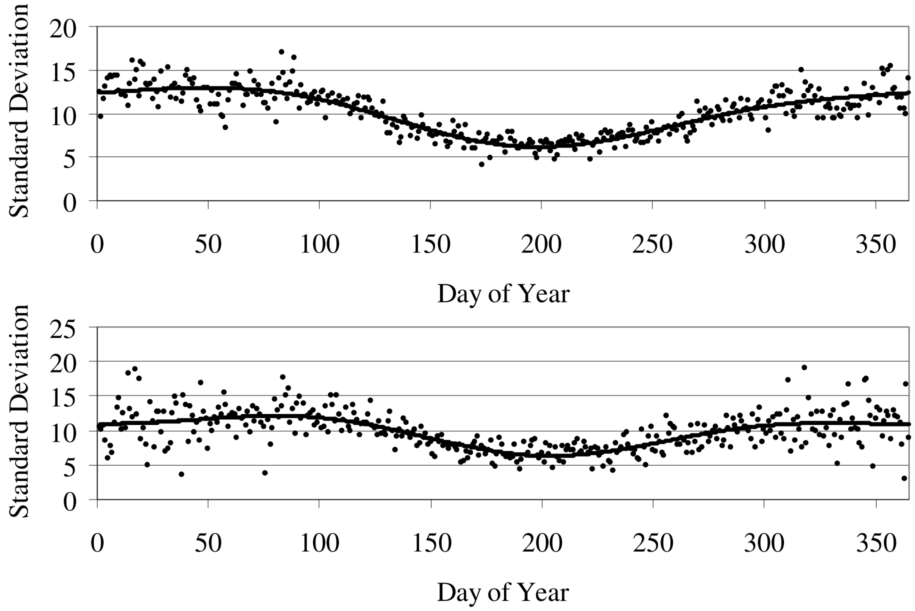

Figure 9. Observed and Fourier series estimated daily standard deviation (°F) of maximum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

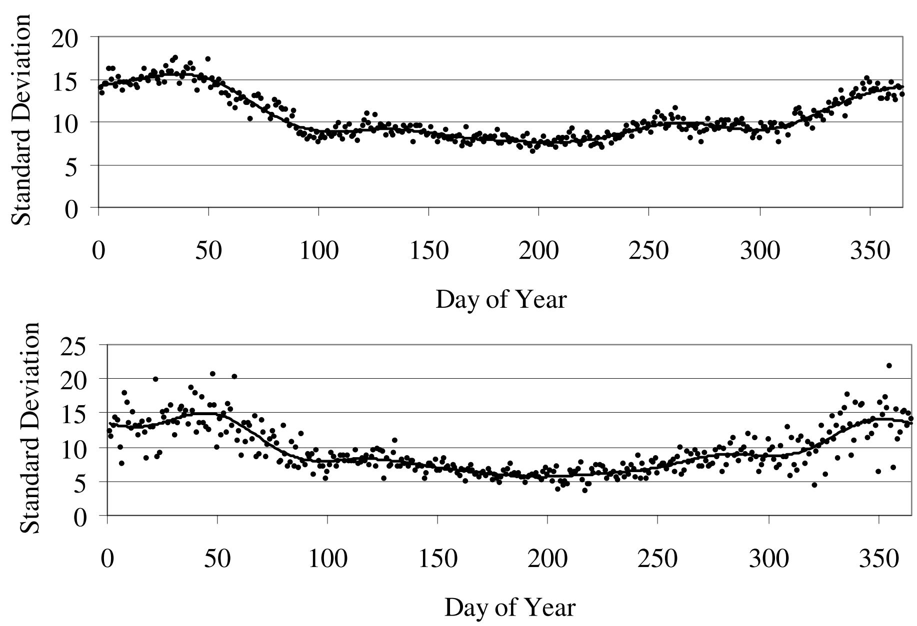

Figure 10. Observed and Fourier series estimated daily standard deviation (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Brookings, SD.

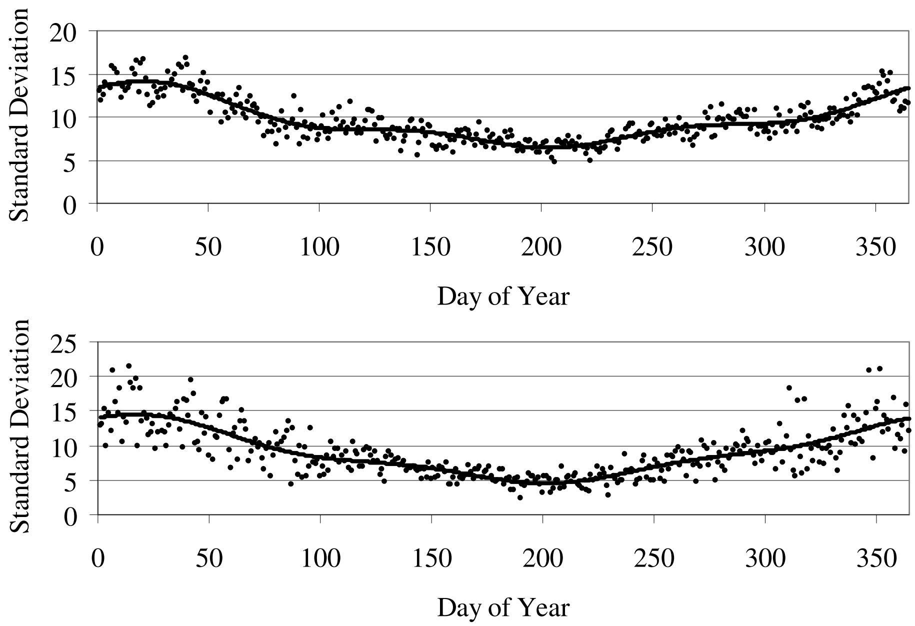

Figure 11. Observed and Fourier series estimated daily standard deviation (°F) of minimum air temperature for a dry day (top) and for a wet day (bottom) for Boone, IA.

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