STOCHASTIC SIMULATION OF DAILY WEATHER VARIABLES

Ju Young Lee , Kelly Brumbelow

School of Environmental and Water Resource Engineering, Department of Civil Engineering, Texas A&M University, College Station, TX 77840

Abstract: Meteorological data are often needed to evaluate the long-term effects of proposed hydrologic changes. The evaluation is frequently undertaken using deterministic mathematical models that require daily weather data as input including precipitation amount, maximum and minimum temperature, relative humidity, solar radiation and wind speed. Stochastic generation of the required weather data offers alternative to the use of observed weather records. The precipitation is modeled by a Markov Chain-exponential model. The other variables are generated by multivariate model with means and standard deviations of the variables conditioned on the wet or dry status of the day as determined by the precipitation model. Ultimately, the objective of this paper is to compare Richardson's model and the improved weather generation model in their ability to provide daily weather data for the crop model to study potential impacts of climate change on the irrigation needs and crop yield. However this paper does not refer to the improved weather generation model and the crop model. The new weather generation model improved will be introduced in the Journal of KWRA.

Keywords: Richardson's Model, Markov Chain, Crop model, Wet day and Dry day

INTRODUCTION

One of major gaps in the generated and observed hydrologic data is the quantification of uncertainty as a result of climatic variability. The meteorological variables needed for most hydrologic models include precipitation, maximum and minimum temperatures, solar radiation, wind velocity and relative humidity. These variables are usually recorded daily, and most deterministic models require daily values. The objective of this study was to develop a technique for simulating daily value of precipitation, maximum and minimum temperatures, solar radiation, wind velocity and relative humidity.

1. Modeling methodology

To make a simulation model, the processes are time dependent within each variable and interdependent among the six variables. The maximum temperature should be continuously correlated because of heat storage and heat transfer from one day to the next. The relationship between radiation and temperature is close. The maximum temperature will likely be high on a sunny day with high solar radiation. The difference between maximum and minimum temperatures will be related because of heat storage and heat transfer in the atmosphere. Heat transfer will obviously be related to wind speed.

The stochastic model can account for interrelations and seasonal variations. Ultimately, this model should be able to provide daily weather data for the crop model to study potential impacts of climate change on the irrigation needs and crop yield.

2. Precipitation

Daily precipitation amounts are determined independently of the other variables. Any precipitation model that produces daily precipitation values can be used for the precipitation component.

Daily precipitation data generation models can be classified broadly into four groups, namely, those with the precipitation occurrence based on the Markov chain-exponential model an alternative renewal processes, transition probability matrix models, resampling models and time series models of the ARMA type(Lee Won-Hwon, 1990). For this study a simple Markov Chain-exponential model was used for the precipitation component for simulating the other weather variables.

Markov chains specify the state of each day as 'wet' or 'dry' and develop a relation between the state of the current day and the state of the preceding days. A first order Markov chain (Bailey, 1964) was used to describe the occurrence of wet or dry days. The order of the Markov chain is the number of preceding days taken into account. The Markov chain referred to in the literature is first order (Gabriel and Newmann, 1962; Caskey, 1963; Weiss, 1964; Hopkins and Robillard, 1964; Feyerherm and Bark, 1965, 1967; Lowry and Guthrie, 1968; Selvalingam and Miura, 1978; Stern, 1980a,b; Garbutt *et al.*, 1981; Richardson, 1981; Stern and Coe, 1984).

For this study a first order Markov chain with only two states, wet or dry, was used. A day with total rainfall of 0.2mm (0.008 in) or a wet day on day t given a wet day t-1; let $\Pr(W_t/W_{t-1})$ be the probability that the process at time t will be in "state" i given that at time t-1 the process was in "state" j such as probability of a wet day on day i given a wet day on day i-1; let $\Pr(W_t/D_{t-1})$; be the probability that the process at time t will be in "state" i given that at time t-1 the process was in "state" j such as probability of a wet day on day i given a dry day on day i-1. Then

$$\Pr(D_t/W_{t-1}) = 1 - \Pr(W_t/W_{t-1}) \tag{1}$$

$$\Pr(D_t/D_{t-1}) = 1 - \Pr(W_t/D_{t-1}) \tag{2}$$

Where $\Pr(D_t/W_{t-1})$ and $\Pr(D_t/D_{t-1})$ are the probability of a dry day given a wet day on day i-1 and the probability of a dry day given a dry day on day i-1, respectively. Therefore these is commonly called the transition probability.

The shape of general distribution of precipitation resembles an exponential distribution. *Todorovic and Woolhiser*(1974) have often used an exponential distribution. The probability density function is

$$p_T(t:\lambda) = \frac{dP_T(t:\lambda)}{dt} = \lambda e^{-\lambda t} \tag{3}$$

and is the probability distribution of the length of the time interval between occurrences of the event. The exponential distribution was simply used to illustrate the technique for simulating the six meteorological variable.

Markov chain transition probabilities $\Pr(W_t / W_{t-1})$ and $\Pr(W_t / D_{t-1})$ and λ are seasonal for most locations. To simulate precipitation, the seasonal nature of these parameters may be described by using Fourier series or other periodic functions.

3. Maximum Temperature, Minimum Temperature, Relative humidity, Wind speed, and Solar radiation

Meteorological variables such as maximum and minimum temperature, relative humidity, wind speed, and solar radiation are not as difficult to apply to the stochastic model as precipitation.

*Joseph(1973) and Nicks(1975)*founded serial correlation and cross correlation in each variables, and developed a model for generating daily values of maximum and minimum temperatures and solar radiation.

Following the procedure described by Yevjevich (1972), assume that daily maximum and minimum temperatures, relative humidity, wind speed, and solar radiation are a continuous multivariate stochastic 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 temperatures, relative humidity, wind speed, and solar radiation separately for wet and dry days. This calculation yields five variables estimates for each day of the year. The time series of each variable was reduced to a time series of residual elements by removing the periodic means and standard deviations. These variables were analyzed to determine serial correlation and cross correlation between each pair of variables. The daily means and standard deviations of five variables were determined for wet days and for dry days using 20 years of data Fourier series were used to smooth the seasonal means and standard deviations. The residual elements were calculated by removing the periodic mean and standard deviation by using the equation;

$$\chi_{p,t}(j) = \frac{X_{p,t}(j) - \overline{X}_t^o(j)}{\sigma_t^o(j)} \qquad Y_{p,t} = 0 \tag{4}$$

or

$$\chi_{p,t}(j) = \frac{X_{p,t}(j) - \overline{X}_t^1(j)}{\sigma_t^1(j)} \qquad Y_{p,t} > 0 \tag{5}$$

Where $\overline{X}_t^o(j)$ and $\sigma_t^o(j)$ are the mean and standard deviation for a dry day, $\overline{X}_t^1(j)$ and $\sigma_t^1(j)$ are the mean and standard deviation for a wet day, and $\chi_{p,t}(j)$ is the residual component for variable j. The residual series for each variable was dependent in time(serial correlation), and the five series were interdependent(cross-correlation).

4. Multivariate Generation Model

Following the method described by Matalas(1967) and Ju Hun Lee(1991), calculate the maximum and minimum temperature, relative humidity, wind speed, and solar radiation residuals for each observation by subtracting the appropriate wet or dry mean and dividing by the appropriate wet or dry standard deviation observed on that day of the year. Next assume that the maximum and minimum air temperature residuals follow a multivariate weakly stationary process defined by:

$$\chi_{p,t}(j) = A\chi_{p,t-1}(j) + B\varepsilon_{p,t}(j) \tag{6}$$

Where $\chi_{p,t}(j)$ and $\chi_{p,t-1}(j)$ are (5×1) matrices of the maximum(j=1) and minimum temperature(j=2), relative humidity(j=3), wind speed(j=4), and solar radiation residuals(j=5) for days t and t-1 of year p; $\varepsilon_{p,t}(j)$ is a (5×1) matrix of independent random components that are normally distributed with a mean of zero and a variance of unity;

A and B are (5×5) 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

The A and B matrices are determined by the matrices equations;

$$A = M_1 M_o^{-1} \quad (7)$$

$$BB^T = M_o - M_1 M_o^{-1} M_1^T \quad (8)$$

M_o and M_1 are the lag 0 and lag 1 correlation matrices. The matrices may be written

$$M_o = \begin{bmatrix} 1 & \rho_{o,(1,2)} & \rho_{o,(1,3)} & \rho_{o,(1,4)} & \rho_{o,(1,5)} \\ \rho_{o,(2,1)} & 1 & \rho_{o,(2,3)} & \rho_{o,(2,4)} & \rho_{o,(2,5)} \\ \rho_{o,(3,1)} & \rho_{o,(3,2)} & 1 & \rho_{o,(3,4)} & \rho_{o,(3,5)} \\ \rho_{o,(4,1)} & \rho_{o,(4,2)} & \rho_{o,(4,3)} & 1 & \rho_{o,(4,5)} \\ \rho_{o,(5,1)} & \rho_{o,(5,2)} & \rho_{o,(5,3)} & \rho_{o,(5,4)} & 1 \end{bmatrix} \quad (9)$$

$$M_1 = \begin{bmatrix} \rho_{1,(1)} & \rho_{1,(1,2)} & \rho_{1,(1,3)} & \rho_{1,(1,4)} & \rho_{1,(1,5)} \\ \rho_{1,(2,1)} & \rho_{1,(2)} & \rho_{1,(2,3)} & \rho_{1,(2,4)} & \rho_{1,(2,5)} \\ \rho_{1,(3,1)} & \rho_{1,(3,2)} & \rho_{1,(3)} & \rho_{1,(3,4)} & \rho_{1,(3,5)} \\ \rho_{1,(4,1)} & \rho_{1,(4,2)} & \rho_{1,(4,3)} & \rho_{1,(4)} & \rho_{1,(4,5)} \\ \rho_{1,(5,1)} & \rho_{1,(5,2)} & \rho_{1,(5,3)} & \rho_{1,(5,4)} & \rho_{1,(5)} \end{bmatrix} \quad (10)$$

where $\rho_{o,(j,k)}$ is the lag 0 cross correlation coefficient between residuals for each variables, $\rho_{1,(j,k)}$ are the lag 1 cross correlation for the residuals of each variables, and $\rho_{1,(j)}$ is the lag 1 serial correlation for variable j.

5. Test of the Model

Daily weather data for Montgomery, Alabama in the U.S, and Sokch'o, South Korea were obtained for testing the stochastic simulation technique. These locations were chosen to include different climatic conditions. Daily values of precipitation, maximum temperature, minimum temperature, relative humidity, wind speed, and solar radiation data were obtained. For each station, 20 years of data were used to estimate six variables.

5.1 Parameter Evaluation

The three parameters of the precipitation model $\Pr(W_t / W_{t-1})$, $\Pr(W_t / D_{t-1})$, and λ were determined for each station. The year was partitioned into 28 day period. The seasonal variation of each parameter was described by using Fourier series. The general equation used for each series is:

$$v_t = C_o + \sum_{j=1}^{m} C_j \cos\left(\frac{\frac{jt}{365}+\theta_j}{2\pi}\right) \quad (11)$$

where v_t is the value of the parameter for day t, C_o is the mean of v_t, and C_j is the amplitude and θ_j the phase angle of the j-th harmonic(*Woolhiser and Pegram,1979*). The estimated coefficients are C_o, C_j, and θ_j, the number of harmonics for the series, and given for each parameter in Table 1. Figure 1 illustrates the fit provided by the Fourier series at both locations.

The daily means and standard deviations of maximum, minimum temperature, relative humidity, wind speed, and solar radiation were

Table1. Fourier series coefficient estimates for Potential Harmonics of the Markov Chain-exponential Precipitation Model in Montgomery, AL in the U.S, and Sokch'o, South Korea

Parameter	C_o	C_1	θ_1	C_2	θ_2
			Montgomery, AL in U.S		
a) $\Pr(W / W)$	0.44	0.03	2.6	0.05	-1.1
b) $\Pr(W / D)$	0.22	−0.04	1.1	-0.05	2.1
λ mm-1	1.317	0.1	0.2	0.2	0.2
			Sokch'o in South Korea		
$\Pr(W / W)$	0.48	0.03	-0.15	-0.14	-0.85
$\Pr(W / D)$	0.2	0.03	2	-0.078	-0.2
λ mm-1	0.1	0.01	-0.03	0.03	-0.6

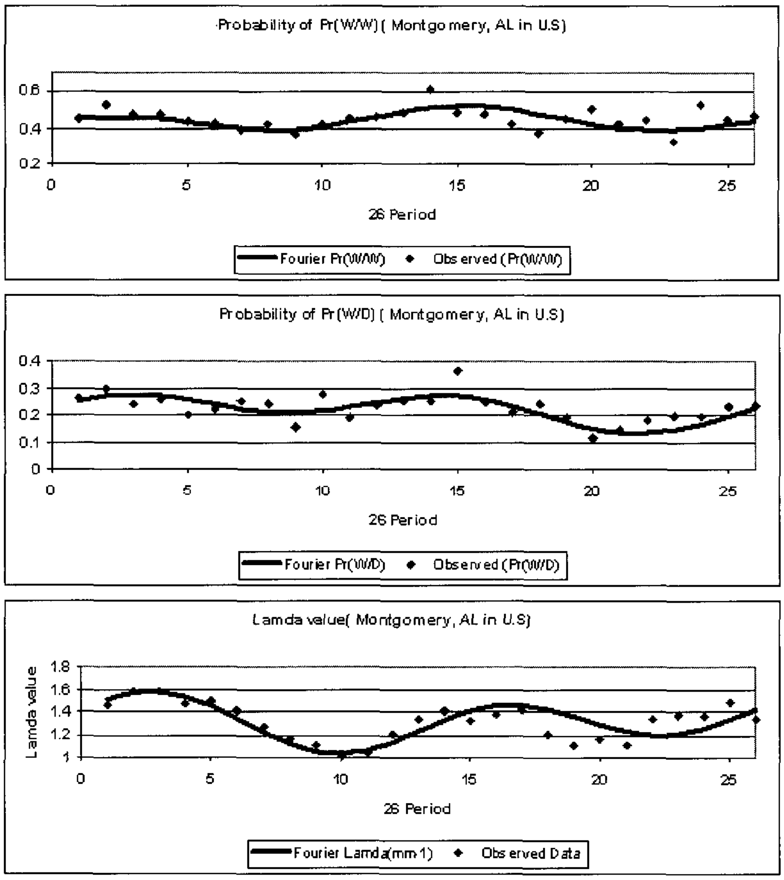

Figure 1. Observed and Fourier series estimates of the Markov Chain-Exponential Precipitation model for $\Pr(W / W)$ (top), $\Pr(W / D)$(bottom), and λ in Montgomery, AL in the U.S.

Table 2. Fourier series coefficient estimates for the mean and standard deviation of the maximum-minimum temperatures, relative humidity, solar radiation and wind velocity on a dry/wet day for Montgomery, AL in the U.S.

Parameter	Wet/Dry	C_o	C_1	θ_1	C_2	θ_2
		Maximum Temperature, ^oC				
Mean	Dry	25	9	2.8	0.5	3
Mean	Wet	24.7	8.5	2.8	0	1
Standard Deviation	Dry	6	3	-0.25	0	0
Standard Deviation	Wet	6	2	-0.2	0.7	-0.5
		Minimum Temperature, ^oC				
Mean	Dry	11	10.8	2.85	0.8	-3
Mean	Wet	14.4	2.7	2.7	-0.5	0.2
Standard Deviation	Dry	6.2	3	-0.2	0.5	1.9
Standard Deviation	Wet	4.5	3.5	-0.2	1	-0.5
		Relative Humidity, %				
Mean	Dry	42	3	2	3.5	-0.5
Mean	Wet	62	7	0	2	0
Standard Deviation	Dry	12	4	-0.25	0	0
Standard Deviation	Wet	13	2	-0.2	0	0
		Solar radiation, hour				
Mean	Dry	8.2	1.5	3	-1.5	-0.2
Mean	Wet	3.75	-2.5	0	-1.5	-0.1
Standard Deviation	Dry	2.83	0.2	-1	0.2	1
Standard Deviation	Wet	2.33	1	-3	0	0
		Wind Velocity mph				
Mean	Dry	6	1	-0.75	0.2	0.5
Mean	Wet	7.3	1.7	-0.5	0.2	0.5
Standard Deviation	Dry	2.3	1	-0.45	0	0
Standard Deviation	Wet	2.1	0.9	-0.5	0	0

Table 3. Fourier series coefficient estimates for the mean and standard deviation of the maximum-minimum temperature, relative humidity, solar radiation and wind velocity on a dry/wet day for Sokch'o, South Korea

Parameter	Wet / Dry	C_o	C_1	θ_1	C_2	θ_2
		Maximum Temperature, $^o C$				
Mean	Dry	16.3	12	9	1	2
Mean	Wet	14	11	2.6	1.3	4
Standard Deviation	Dry	3.9	1.2	-1.2	0.7	0.4
Standard Deviation	Wet	3	-0.7	0.3	0.9	0.9
		Minimum Temperature, $^o C$				
Mean	Dry	8.7	13.5	2.7	0.8	1
Mean	Wet	8.7	11.2	2.6	1.6	4.5
Standard Deviation	Dry	3.3	0.8	-0.2	-0.4	3.4
Standard Deviation	Wet	2.2	0.5	0.2	0.3	0.8
		Relative Humidity, %				
Mean	Dry	64	17	-9.7	-2	2
Mean	Wet	80.5	6	3	1	5
Standard Deviation	Dry	14.4	3	-1.2	-3	5
Standard Deviation	Wet	12.5	6	-1	1	2.5
		Solar radiation, hour				
Mean	Dry	7.4	1	4	-0.6	-1
Mean	Wet	2.27	0.4	-0.5	0.7	-1
Standard Deviation	Dry	3.3	-1	0.1	0	-2
Standard Deviation	Wet	3.3	-0.3	1	1	2
		Wind Velocity mph				
Mean	Dry	3.12	0.6	-0.6	-0.4	-2
Mean	Wet	3	0.7	-0.8	-0.2	-0.7
Standard Deviation	Dry	1.24	0.5	-0.2	0.3	1
Standard Deviation	Wet	1.56	0.1	1	0.2	2

Table 4. Mean, standard deviation, skewness coefficient, and kurtosis coefficient of the residuals of maximum-minimum Temperatures, relative humidity, Solar radiation, and wind speed

Variable	Mean	Standard Deviation	Skewness Coefficient	Kurtosis Coefficient
		Montgomery, AL in the U.S		
Maximum Temperature	0.03	1.01	-0.493	3.468
Minimum Temperature	-0.01	1.04	-0.508	2.663
Relative Humidity	-0.04	1.05	0.209	1.049
Solar Radiation	-0.04	1.01	-0.276	2.406
Wind Speed	-0.05	1.05	0.809	2.283
		Sokcho'o, in South Korea		
Maximum Temperature	0.049	1.04	0.355	2.779
Minimum Temperature	-0.031	1.03	0.143	2.321
Relative Humidity	-0.037	1.04	-0.660	2.194
Solar Radiation	0.001	0.96	-0.337	2.014
Wind Speed	0.036	1.03	1.75	3.212

calculated for each wet or dry of day. The C_j, and θ_j values are given in Table 2 and 3 for the two stations.

The residuals, $\chi_{p,i}(j)$, were calculated by using (4) for each variable. The mean and standard deviations used in (4) were obtained from the Fourier series representation. For new generation of residual, the residual should be approximately normal distribution using (5).

The serial dependence of the residuals should be seen in the first order linear autoregressive model. The serial correlation of a first-order autoregressive model is given by $\rho_k = \rho_1^k$, where ρ_k is the serial correlation for lag k.

The mean, standard deviation, skewness coefficient, and kurtosis coefficient were calculated for residuals and are shown in Table 4. The results show that the use of (4) did reduce the series to residuals with a mean near zero and a standard deviation near unity.

The skewness coefficients of the residual series were positive and negative but were near the zero that should be obtained from normal distribution. The Kurotosis coefficients were also all near a value of 3, which is indicative of a normal distribution.

The serial correlation coefficients were calculated for each residual series for lags up to 10 days. The serial correlation coefficients were compared to a first order autoregressive model with $\rho_1 = r_1$, where r_1 is the lag 1 serial cor relation coefficient from residual series. The results for Sokch'o data are shown in Figure 2. For five of the variables the series correlation coefficient was similar for a first-order model.

The interdependence among the variables wasdetermined by calculating the lag cross correlation coefficients are shown in Table 5.
The cross correlation coefficients of the observed and generated data are illustrated in Figure 3 for Sokch'o in South Korea

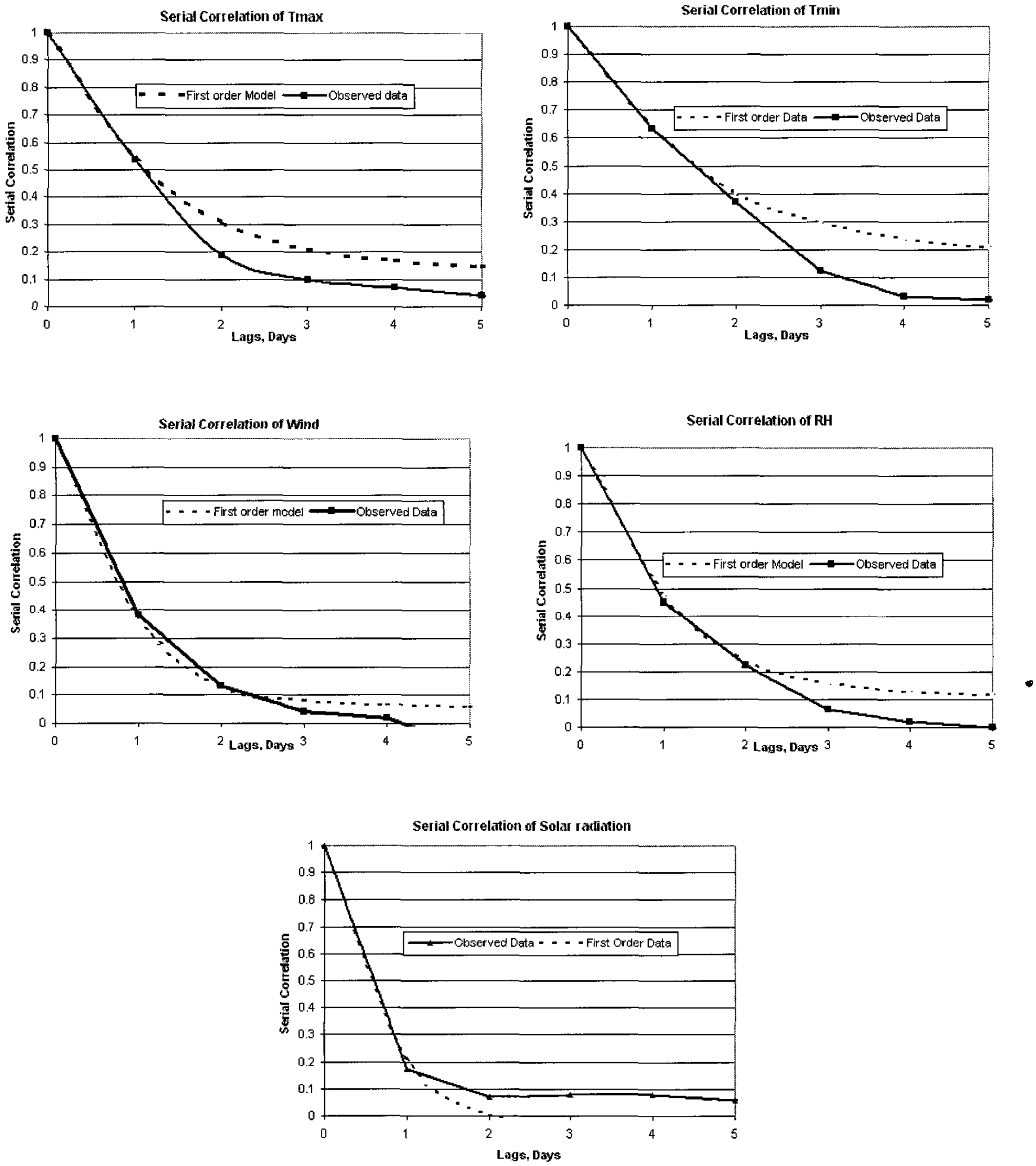

Figure 2. Serial correlation coefficients of maximum-minimum temperatures, relative humidity, solar radiation, and wind speed for Sokch'o, South Korea.

Table 5. Cross-correlation coefficients of maximum-minimum temperatures, relative humidity, solar radiation, and wind speed for Montgomery, AL in the U.S and Sokch'o, South Korea

Variables	Lag Cross Correlation		
	$r_1(j,i)$	$r_0(i,j)$	$r_1(i,j)$
Montgomery, AL in the U.S			
Maximum-Minimum Temperature	0.498	0.517	0.375
Maximum-Relative Humidity	-0.049	-0.205	-0.088
Maximum-Solar Radiation	-0.003	0.180	0.115
Maximum-Wind Speed	-0.013	-0.226	-0.318
Minimum-Relative Humidity	0.249	0.405	0.284
Minimum-Solar Radiation	-0.165	-0.313	-0.209
Minimum-Wind Speed	0.078	0.053	-0.128
Relative Humidity-Solar Radiation	-0.240	-0.652	-0.240
Relative Humidity-Wind Speed	0.098	0.118	-0.014
Solar Radiation-Wind Speed	-0.122	-0.093	0.030
Sokch'o, South Korea			
Maximum-Minimum Temperature	0.528	0.682	0.472
Maximum-Relative Humidity	-0.104	-0.203	-0.033
Maximum-Solar Radiation	0.006	0.164	0.089
Maximum-Wind Speed	0.059	-0.009	-0.098
Minimum-Relative Humidity	0.016	-0.014	0.016
Minimum-Solar Radiation	-0.072	-0.059	0.022
Minimum-Wind Speed	0.010	-0.053	-0.139
Relative Humidity-Solar Radiation	-0.169	-0.337	-0.208
Relative Humidity-Wind Speed	-0.182	-0.333	-0.267
Solar Radiation-Wind Speed	0.003	0.109	0.110

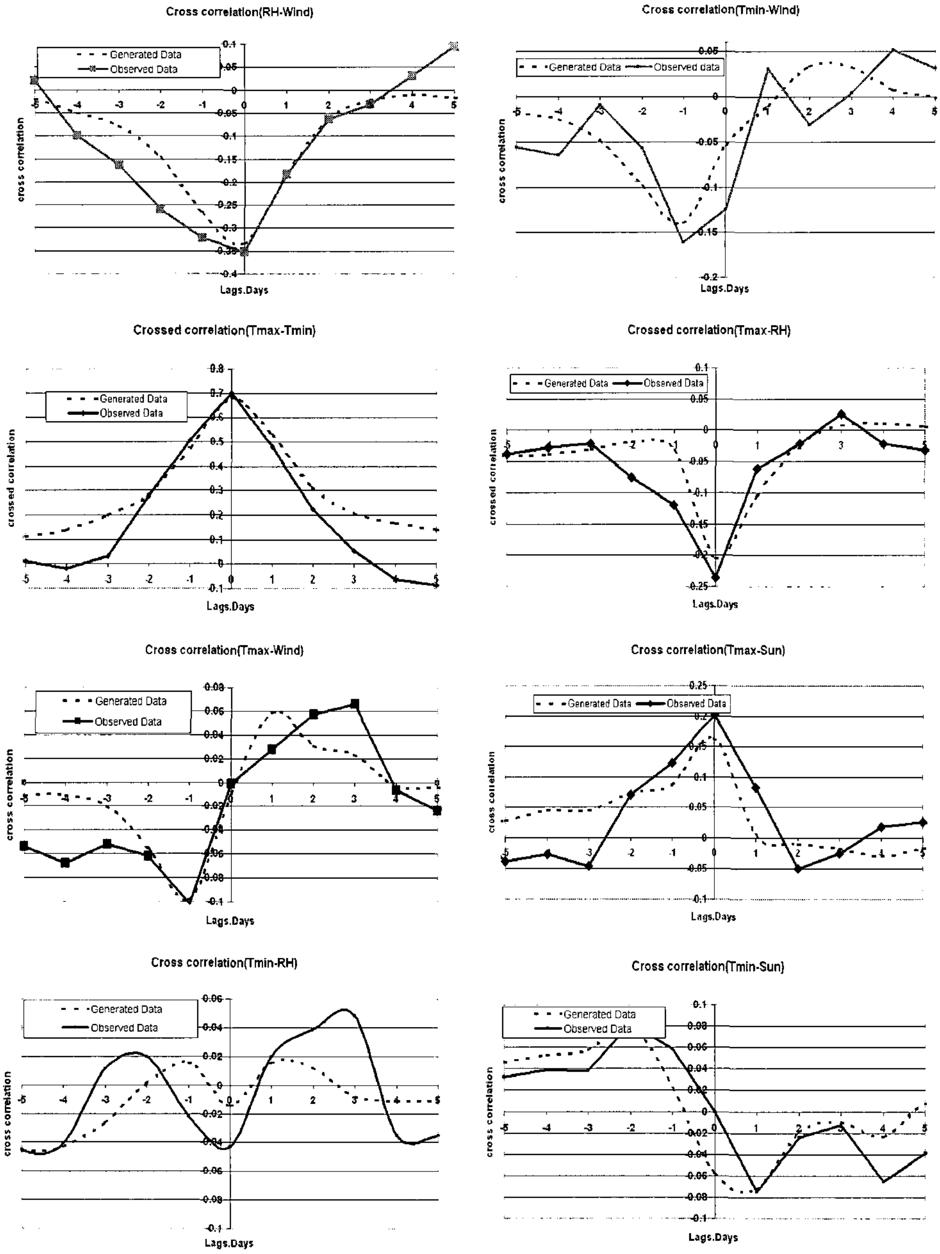

Figure 3. Cross correlation coefficients obtained from observed and generated weather variables for Sokch'o. South Korea.

Table 6. Mean daily maximum-minimum temperatures, relative humidity, wind speed, and relative humidity for a 28 day period and for the year at Montgomery, AL in the U.S.

Period	Maximum Temperature, *F*(Dry Day)		Maximum Temperature, *F*(Wet Day)	
	Obseved	Generated	Obseved	Generated
1	56.5	57.4	58.1	61.7
2	62.6	60.8	63.6	62.8
3	69.9	68.2	66.4	66.9
4	76.5	76.8	74.3	73.3
5	82.9	86.8	81.8	80.4
6	89.0	89.5	86.9	86.6
7	92.9	92.4	89.7	90.5
8	93.3	93.0	90.4	91.1
9	91.7	90.8	89.9	88.6
10	87.0	85.2	82.8	83.2
11	77.8	76.6	76.1	76.3
12	68.4	67.0	71.4	69.4
13	60.8	59.7	61.5	64.1
Year	77.6	77.0	76.3	76.5

Period	Maximum Temperature, *F*(Dry Day)		Maximum Temperature, *F*(Wet Day)	
	Obseved	Generated	Obseved	Generated
1	32.2	32.7	42.4	44.2
2	36.9	34.1	46.1	45.2
3	42.3	39.3	48.8	49.1
4	48.4	47.4	53.3	55.2
5	56.6	56.7	62.2	61.6
6	64.3	65.3	67.7	67.4
7	69.5	70.9	70.8	71.1
8	70.9	72.1	71.3	71.7
9	69.5	68.4	70.8	69.3
10	60.7	60.8	65.4	64.2
11	49.3	51.2	58.0	57.8
12	41.4	42.2	53.1	51.4
13	35.9	35.5	44.4	46.4
Year	55.1	52.0	57.9	58.8

Period	Maximum Temperature (Dry Day), %		Maximum Temperature (Wet Day), %	
	Obseved	Generated	Obseved	Generated
1	40.0	43.5	63.9	70.4
2	36.9	41.2	64.0	67.4
3	34.6	37.9	60.2	63.0
4	36.0	36.2	54.1	59.3
5	40.0	39.7	57.6	57.4
6	42.6	42.2	57.0	57.0
7	44.4	46.2	58.2	57.0
8	47.2	47.4	58.2	57.0
9	47.2	45.4	56.6	57.4
10	42.0	42.4	60.7	59.3
11	39.8	40.8	60.5	63.0
12	40.3	41.6	66.4	67.4
13	43.5	43.3	65.3	70.4
Year	41.1	42.0	60.2	62.0

Period	Maximum Temperature (Dry Day), min		Maximum Temperature (Wet Day), min	
	Obseved	Generated	Obseved	Generated
1	391	403	84	64
2	428.1	430.8	87.7	105.4
3	536.3	471.4	144.6	171.6
4	568.8	516.3	235.7	238.8
5	553.9	555.2	254.9	292.6
6	529.9	579.2	252.1	330.3
7	563.3	582.9	307.6	353.7
8	553.5	565.4	332.4	359.4
9	499.1	530.8	306.5	338.0
10	547.6	486.8	214.6	283.3
11	452.1	443.6	109.2	203.2
12	412.4	411.0	87.5	121.8
13	361.3	396.3	58.7	68.4
Year	491.8	490.0	189.2	225.0

Period	Wind Speed(Dry Day), m/s Obseved	Generated	Wind Speed(Wet Day), m/s Obseved	Generated
1	6.9	7	7.6	9
2	7.1	6.9	8	8.8
3	7.3	6.7	9.0	8.4
4	6.6	6.4	8.1	7.8
5	5.7	6.2	7.1	7.1
6	5.4	5.8	6.2	7.0
7	5.1	5.1	5.2	5.6
8	5.2	4.9	5.7	5.6
9	5.2	5.1	6.5	6.1
10	5.3	5.2	6.0	6.0
11	4.8	5.6	7.6	6.0
12	5.6	6.2	7.7	8
13	6.0	6.7	7.3	8.7
Year	491.8	490.0	189.2	225.0

5.2 Weather Variable Simulation

The generation of the precipitation data was obtained by using the Markov Chain-exponential model and the parameters of the precipitation model were obtained from the Fourier series in Table 1.

The serial correlation and cross correlation coefficients define matrices M_0 and M_1. These are required for the multivariate generation of the residuals of maximum-minimum temperatures, relative humidity, solar radiation, and wind speed. The seasonal means and standard deviations of the five variables for wet and dry days were obtained from the Fourier series.

Twenty years of daily precipitation, maximum, minimum temperature, relative humidity, wind speed and solar radiation data were generated to compare with observed data of two stations.

The maximum-minimum temperatures, relative humidity, wind speed and solar radiation data generated were compared with the observed data in Table 6-7.

The generated means for all five variables for each period of the year were comparable with the observed means and gave a good description of the seasonal variation of the variables.

The difference between the generated data and observed data were thought to be due to the Fourier series smoothing of the generated data.

SUMMARY AND CONCLUSIONS

This paper describes the use of models to generate a simulated time series of weather variables.

To generate a model, the precipitation is made independent of other five variables and then the five variables conditioned on the wet or dry status of the day are generated.

For the precipitation model, a Markov chain-exponential model was used to describe precipitation.

The multivariate model was used to describe maximum-minimum temperature, relative humidity, solar radiation and wind speed.

The model showed that generated data can represent the characteristics that existed in the interdependence among the variables and are closely described by the dependence structure using eq. (6).

The skewness coefficient and Kurtosis coefficient could be used to determine normal distribution or non-normal distribution.

Acknowledgements

This paper is along the lines of Richardson's work and verifies the study of Richardson's model. The objective of this project is to compare Richardson's model and the improved weather generation model. The improved weather generation model improved will be introduced in the Journal of KWRA.

REFERENCES

Bailey, N.T. J., *The Elements of Stochastic Processes*, p.39, John Wiley, New York, 1964.

Caskey, J. E., Jr., A Markov chain model for the probability of precipitation occurrence in intervals of various lengths, *Mon. Weather Rev*., 91, 298-301, 1963

Feyerherm, A.M. and Bark, L.D., 1965. Statistical methods for persistent precipitation pattern. *J. Appl. Meteorol.*, 4, 320–328.

Feyerherm, A.M. and Bark, L.D., 1967. Goodness of fit of Markov chain model for sequences of wet and dry days. *J. Appl. Meteorol.*, 6, 770–773.

Gabriel, R., and J. Neuman, A Markov chain model for daily rainfall occurrence at Tel Aviv, Israel, *Q. J. R Meteorol, Soc*., 88, 90-95, 1962

Garbutt, D.J., Stern, R.D., Dennet, M.D. and Elston, J., 1981. A comparison of rainfall climate of eleven places in West Africa using a two-part model for daily rainfall. *Arch. Met. Geoph. Biokl., Ser. B.,* 29, 137–155.

Hopkins, J. W., and P. Robillard, Some statistics of daily rainfall occurrence for the Canadian prairie province, *J. appl. Meteorol*., 3, 600-602, 1964.

Joseph, E. S., Spectral analysis of daily maximum and minimum temperature series on the east slope of the Colorado Front Range, *Mon. Weather Rev*., 101(6), 505-509, 1973

Lowry, W.P. and Guthrie, D., 1968. Markov chains of order greater than one. *Mon. Weath. Rev.*, 96, 798–801.

Matalas, N.C., 1967. Mathematical assessment of synthetic hydrology. *Water Resour. Res*., 3, 937–945.

Nicks, A. D., *Stochastic generation of hydrologic model inputs*, Ph.D. dissertation, 142 pp., Univ. of Okla., Morman, 1975.

Richardson, C.W., 1981. Stochastic simulation of daily precipitation, temperature and solar radiation. *Water Resour.Res*., 17, 182–190.

Selvalingam, S. and Miura, M., 1978. Stochastic modelling of monthly and daily rainfall sequences. *Water Resour. Bull.*, 14, 1105–1120.

Stern, R.D. and Coe, R., 1984. A model fitting analysis of daily rainfall data. *J. Roy. Statist. Soc. A*, 147, Part 1, 1–34.

Todorovic, P., and D. A. Woolhiser, Stochastic model of daily rainfall, Proceedings of the Symposium on Statistical Hydrology, *Misc. Publ.* 1275, pp. 223-246, U.S. Dep. of Agric., Washington, D. C., 1974.

Weiss, L. L., Sequence of wet and dry days described by a Markov chain probability model, *Mon. Weather Rev*., 92, 169-176, 1964

Woolhiser, D.A. and Pegram, G.G.S., 1979.

Maximum likelihood estimation of fourier coefficients to describe seasonal variation of parameters in stochastic daily precipitation models. *J. Appl.Meteorol.*, 18, 34–42.

Yevjevich. V., Structural analysis of hydrologic time series, *Hydrol. Pap*. 56, 59 pp., Colo. State Univ., Fort Collins, 1972

Lee, Joo-Heon, Lee Eun-Tae, 1991, A Comparative Study on the Multivariate Thomas-Fiering

and Matalas Model, Journal of Korean of Korean Association of Hydrological Sciences 1991,12 v.24, n.4, pp.59-66 1226-1408

Lee Won-Hwan, Shim Jae-Hyun,1990, A Comparison of Univariate and Multivariate AR Models for Monthly River Flow Series,

Journal of Korean of Korean Association of Hydrological Sciences, 1990, 03 v.23, n.1, pp.99-107 1226-1408

Texas A&M University, Dept. of Civil Engineering, 3136 TAMU

(E-mail : *wayincrezki@hanmail*)

Texas A&M University, Dept. of Civil Engineering, 3136 TAMU, (979)458-2678,College Station, TX77846, USA