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Comparing Different Weather Generator Algorithms for Daily Temperature

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ABSTRACT

Weather Generators (WGs) are widely used in water engineering, agriculture, ecosystem and climate change studies because observed climatic series have deficiencies related to length, completeness and spatial coverage. WG models can simulate daily temperature data in a few parametric ways. One way is to simulate daily minimum (*Tmin*) and maximum (*Tmax*) temperatures using an autoregressive model. Another way consists of the simulation of daily average temperature (*Tav*) and daily temperature range (*R*) and then the calculation of *Tmin* and *Tmax* indirectly. In this study, four different algorithms were assessed for daily temperature in combination with a well-tested weather generator. M1 and M2 algorithms simulated the daily *Tav* and *R* values directly and *Tmin* and *Tmax* indirectly. M3 algorithm simulated *Tmin* and *Tmax* and M4 algorithm simulated *Tmin* and *Tav* directly and the other variables indirectly. The results showed that each algorithm could perform better in simulating primary variables (which are simulated directly). This issue was more considerable in relation to daily *R* values. M2 overestimated the cross-correlation coefficients of this variable because of the assumption of a strong autocorrelation structure between primary variables in the WG model. M3 and M4 outperformed the other algorithms in relation to most studied indices. This study showed the importance of choosing the best temperature generation algorithm according to the requirements.

Introduction

Crop simulation models are used increasingly for predicting the impacts of climatic change and climatic variability on crop growth and yield (Ababaei 2012; Ababaei *et al.* 2010; Soltani *et al.* 2000; Boote *et al.* 1996; Matthews *et al.* 1997; Lal *et al.* 1998). The quality of model outputs is related to the quality of weather data used as input and sensitivity analysis of model output to the quality of generated weather data is essential (Soltani *et al.* 2000). In most crop models, daily temperature is one of the driving forces and is very important to be estimated accurately.

Weather Generators (WGs) are widely used in water engineering, agriculture, ecosystem and climate change studies because observed climatic series have deficiencies related to length, completeness and spatial coverage. These models can fill missing data and are able to reproduce important statistical properties of observed time series. The simulation of daily climatic time series is the most important and usual application of these models. To date, most models have their focus on precipitation as the most important variable affecting environmental processes (Hutchinson 1995). Nonetheless, supplementary algorithms have been also proposed to simulate other variables. In combination with crop simulation models, the accurate simulation of crop production requires synthetic data which can mimic the daily variations of climatic variables (Ababaei *et al*. 2010b; Nonhebel 1994; Semenov and Porter 1995; Semenov *et al.* 1998).

Daily temperature can be simulated in a few parametric ways. One way is to use the method applied in some well-known WG models like LARS-WG (Semenov and Barrow 2002), WGEN (Richardson and Wright 1984) and WeaGETS (Chen *et al*. 2012) and simulate daily minimum (*Tmin*) and maximum (*Tmax*) temperatures using an autoregressive model. Another way consists of the simulation of daily average temperature (*Tav*) and daily temperature range (*R*) and then the calculation of *Tmin* and *Tmax* indirectly. Recently, non-parametric approaches (e.g. Lall and Sharma 1996; Sharif *et al*. 2007) have been utilizing for this purpose.

Since the authors didn’t find any thorough assessment and comparison between these two parametric approaches in simulating daily temperature data, the aim of this paper is to do the assessment to find out what is the difference between these methods.

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Methods and Materials

Methodology

In this research, four different temperature generation algorithms were compared using a well-tested weather generator model. These algorithms include: (1) M1: generation of *Tav* and log-transformed *R*, (2) M2: generation of *Tav* and square-root transformed *R*, (3) M3: generation of *Tmin* and *Tmax* and (4) M4: generation of *Tmin* and *Tav*. After generating the primary variables, secondary variables were estimated using Equations (1) through (5):

$$T_{\min} = T_{av} - R \qquad \text{used in: M1 and M2}$$

$$T_{\max} = T_{av} + R \qquad \text{used in: M1 and M2}$$

$$T_{\max} = 2T_{av} - T_{\min} \qquad \text{used in: M4}$$

$$R = 0.5 * (T_{\max} - T_{\min}) \qquad \text{used in: M3 and M4}$$

$$T_{av} = 0.5 * (T_{\max} + T_{\min}) \qquad \text{used in: M3}$$

The algorithms were assessed in Qazvin station located in Qazvin Province of Iran.

Daily Precipitation Occurrence

One of the most common methods to simulate precipitation in one station is using a precipitation occurrence simulation model and then generating the precipitation quantity on wet days from an independent distribution (Woolhiser 1992). Precipitation occurrence is mostly simulated by two different mechanisms: (1) a Markov process (Gabriel and Neumann 1962; Salas 1993; Katz and Zheng 1999), or (2) an alternating renewal process (ARP) (Buishand 1978; Sharma and Lall 1999). In this study, an ARP process (named PGEN) is utilized, similar to the one which is implemented in LARS-WG (Semenov and Barrow, 2002). Dry and wet spell lengths are generated from monthly semi-empirical distributions (SEDs). Each type of spells is generated after the other one. This method is used in all the models study here. In other words, all the models use the same precipitation occurrence series.

Daily Weather Generator

The daily weather generator (Ababaei, 2012) uses a method similar to the one implemented in LARS-WG (Semenov and Barrow, 2002) which has been evaluated in different climates in Iran (Ababaei *et al*., 2010a). This model uses *SED*s instead of normal distributions (which are used in WGEN-like models). Standard variables selected from *SED*s are then scaled into correlated standard variables using a 4-variable first-order autoregressive model (Equation 6):

$$z(t) = [A]z(t-1) + [B]\varepsilon(t)$$

Where *z(t)*: Gaussian standard variables for day *t*, *A* and *B*: coefficient matrices (Matalas, 1967) and $\varepsilon(t)$: white-noise variables. Afterwards, these standard variables are scaled back to nonstandard variables using long-term daily average and *STD* of each variable for each calendar month (Equation 7):

$$T_k(t) = \begin{cases} \text{Dry Day}: M_{k,0}(t) + ST_{k,0}(t) z_k(t) \\ \text{Wet Day}: M_{k,1}(t) + ST_{k,1}(t) z_k(t) \end{cases}$$

Where *Tk(t)*: the climatic variable *k* on day *t*, *M* and *ST*: the average and (total) *STD* and the indices 0 and 1 indicate dry and wet days, respectively. This step is carried out for wet and dry days separately. Precipitation is generated from an independent SED and is scaled to a nonstandard variable using Equation (7).

Adjusting Low-Frequency Variances

Application of WG models usually results in the underestimation of variances and/or biased estimation of average values of agriculture or hydrological model outputs (Ababaei *et al.* 2010; Hansen and Mavromatis, 2001; Richardson, 1985; Jones and Thornton, 1997; Semenov and Porter, 1995; Mearns *et al*., 1996). For a series including *a* years and each year consisting of n_i daily data (i = 1...*a*) of weather variable *y*, for each month, total standard deviation (*ST*) of *y* can be estimated by Equation (8):

$$ST = \sqrt{\frac{\sum_{i=1}^{a}\sum_{j=1}^{ni}(y_{ij}-\bar{Y})^2}{\sum_{i=1}^{a}(ni-1)}}$$

This total standard deviation can be divided into two elements (Hansen and Mavromatis, 2001): (1) high-frequency *STD* (*SH*) which is related to days within a month (Equation 9), and (2) low-frequency *STD* (*SL*) which is related to the interannual *STD* of each month (*STD* of monthly means, Equation 10):

$$SH = \sqrt{\frac{\sum_{i=1}^{a}\sum_{j=1}^{ni}(y_{ij}-\bar{y}_i)^2}{\sum_{i=1}^{a}(ni-a)}}$$

$$SL = \sqrt{\frac{1}{a-1}\left[\left(\sum_{i=1}^{a}ni-1\right)ST^2-\left(\sum_{i=1}^{a}ni-a\right)SH^2\right]}$$

Many WG models which are used in agriculture and water resources studies simulate *ST* using short-term stochastic processes and are unable to reproduce low-frequency variances like them related to ENSO (Hansen and Mavromatis, 2001). This issue reveals the need for changing interannual properties of climatic variables in order for reproducing these low-frequency variations well. Some methods have been proposed (e.g. Katz and Parlange 1993; Jones and Thornton 1993) and a review can be found in Dubrovsky *et al.* (2004).

In order to improve the performance of the WG models in relation to the interannual variances (low-frequency variances), the series of monthly mean and *STD* values of the climatic variables are constructed for all the months in the entire period (for wet and dry days separately). These series are then scaled (Equation 11) in a way that their average and *STD* values become equal to the observed values:

$$Y = (X-\bar{X})\times\frac{\sigma_Y}{\sigma_X}+\bar{Y}$$

Where *X*: the simulated monthly mean or *STD* values, $\bar{X}$: the mean value of the simulated monthly mean or *STD* series, $\bar{Y}$: the mean value of the observed monthly mean or *STD* series, and σ : the *STD* of these series. Afterwards, daily time series are scaled by an equation similar to Equation (7). This process is carried out for dry and wet days separately.

Model Assessment

For assessing the WG model, 300 years of synthetic time series were generated. For precipitation, the assessment was carried out based on two guiding principles (Ng and Panu 2010): (1) model capability in simulating short-term dependencies, and (2) model capability in simulating dry and wet spells. In relation to the first-order short-term dependencies, the occurrence probability of a wet day after a dry day (Pdw) and a wet day after a wet day (Pww) were compared. In relation to dry and wet spells, the comparisons were carried out using 3-months sliding windows (Dec-Jan-Feb, Jan-Feb-Mar …). The minimum values of daily precipitation of the wet days were set to 0.5 mm. In relation to the other variables, monthly mean and *STD*, different percentiles, interannual mean (the average of the monthly mean values), interannual *STD* (the *STD* of the monthly mean values), daily lag-1 autocorrelation and monthly lag-1 autocorrelation were estimated and compared between the observed and the generated time series. In order to assess the proposed methods, the average (*XErr*) values of Standardized Mean Absolute Errors (*SMAE*) and Standardized Root Mean Square Errors (*SRMSE*) were utilized:

$$SRMSE = \left[\frac{\sum_{i=1}^{n}(P_i-O_i)^2}{n}\right]^{0.5}\times\frac{100}{\bar{O}}$$

$$SMAE = \frac{\sum_{i=1}^{n} | P_i - O_i |}{n} \times \frac{100}{\overline{O}}$$

$$XErr = \frac{SMAE + SRMSE}{2}$$

In which, P_i and O_i are generated and observed values, respectively, $\overline{O}$ is the average observed value and n is the number of values to be compared.

Results and Discussions

Precipitation Occurrence

All algorithms used a similar precipitation occurrence series. As precipitation occurrence affects the monthly statistics of other variables, it was necessary to assess the performance of the WG model from this viewpoint. Figure 1 shows the model performance for the short-term autocorrelations in precipitation time series and also the simulation of wet and dry spells. This figure shows that the model is very accurate in reproducing the precipitation statistics in almost all calendar months, although there are some deficiencies in July to September.

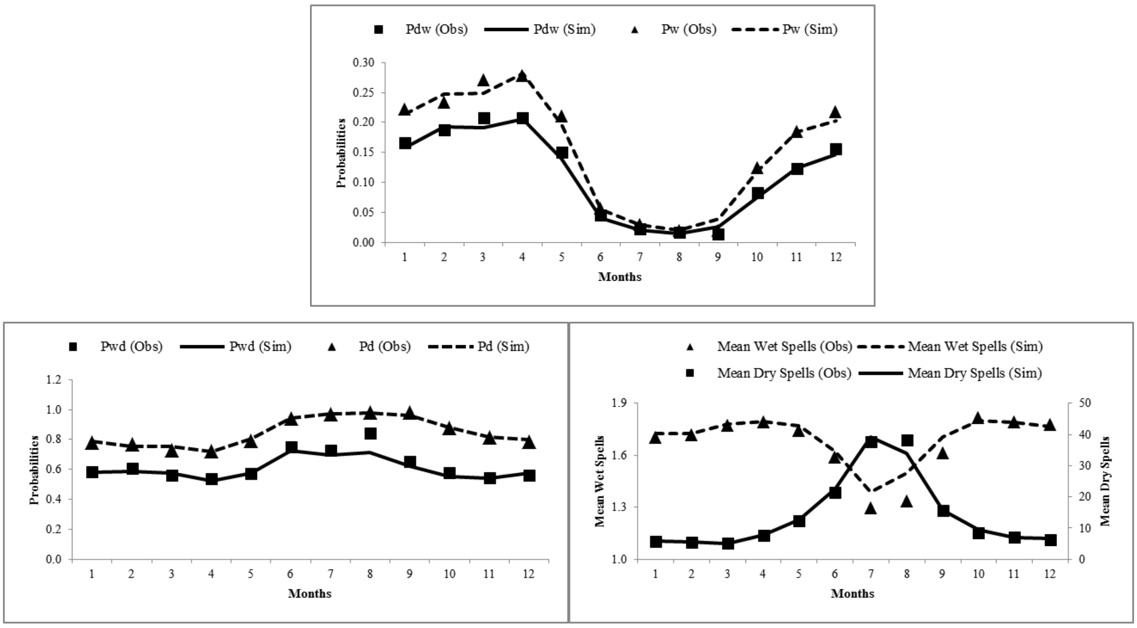


Figure 1- Model performance related to the simulation of precipitation occurrences.

Precipitation Amount

As the WG model uses an adjustment algorithm for low-frequency variations and this algorithm considers the monthly correlations between precipitation and other variables, it was expected that the temperature generation algorithms had different performances in terms of precipitation. Table 1 shows the XErr values of the four algorithms for the simulation of precipitation quantities. The algorithms had comparable performance related to the daily precipitation statistics. But, M3 had the highest XErr values in relation to percentiles. On the whole, it can be concluded that the choice between different temperature generation algorithms affects the simulation of precipitation, but the differences were not considerable.

Table 1, **The XErr values related to the simulation of precipitation quantities**

	M1	M2	M3	M4
Daily Pcp: Mean	4.3%	2.8%	3.4%	2.5%
Daily Pcp: Std	7.6%	6.6%	7.2%	5.5%
Daily Pcp: Skew	6.2%	7.5%	7.6%	9.7%
Daily Pcp: Percentiles	15.1%	14.3%	18.3%	15.1%
Total Monthly Pcp: Mean	7.2%	6.1%	6.5%	6.1%
Total Monthly Pcp: Std	21.0%	17.8%	21.3%	18.9%
Average	10.2%	9.2%	10.7%	9.6%

Temperature: Monthly Statistics

All algorithms performed perfectly in relation to monthly mean values. Figure 2 shows the monthly STD values of temperature variables resulted from all generation algorithms. All algorithms simulated the monthly STD values of *Tmin* very well. But, M4 which directly simulated *Tmin* and *Tav* overestimated the monthly STD values of *Tmax*. A similar conclusion can be made for M3 and M4 and the simulation of the monthly STD values of *R*, since these two models simulated the daily *R* values indirectly. Generally, all models performed acceptably in relation to monthly STD values.

Figure 3 shows the comparisons between observed and simulated percentiles of studied variables resulted from different temperature generation algorithms. All algorithms performed very well in simulating the distribution shape of *Tmin*, *Tmax* and *Tav*. But, the performance of M3 and M4, which simulated *R* values indirectly, was not as well. Both algorithms underestimated the lower tail of the distributions and overestimated the higher tails. This happened because these algorithms simulated the daily *R* values indirectly and independently. This issue can be detected also in Figure 4. M1 and M2 underestimated the monthly maximum values of *Tav* and *R*. But, the other algorithms had deficiencies in relation with the monthly maximum (and minimum) values of *Tav* and *R*.

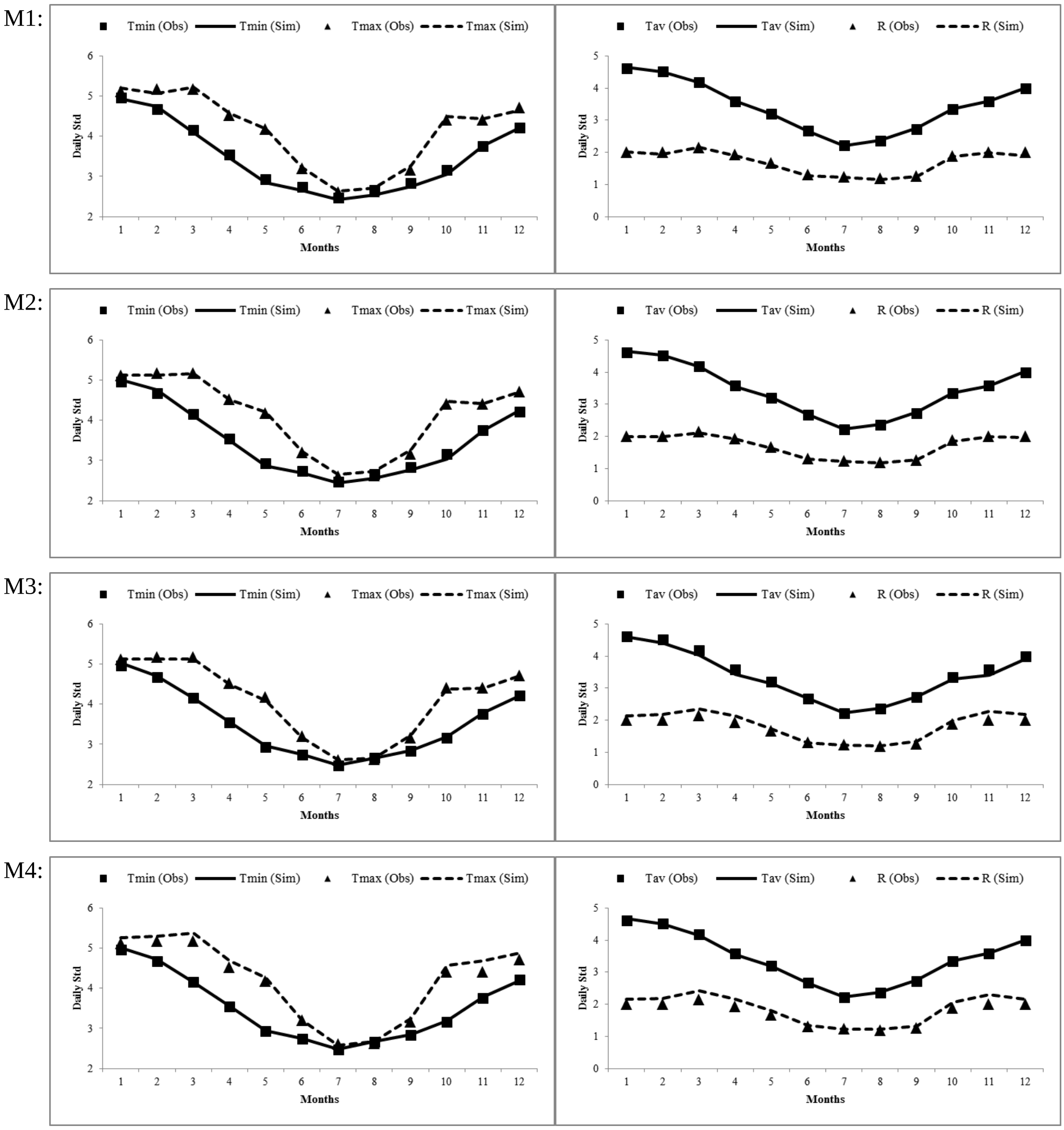


Figure 2- The monthly standard deviation values.

Temperature: Interannual Monthly Statistics

Figure 5 shows the observed and simulated interannual STD values of monthly means. All algorithms performed consistently in reproducing the interannual STD values of *Tmin* and *Tmax*, specially M3 and M4. M1 and M2 algorithms performed well in relation to *Tav* and *R*. But, M3 and M4 underestimated the interannual STD values of *Tav* and specially *R*. This issue happened because the WG model adjusts the SL values for primary variables and this doesn't happen directly for the secondary variables (i.e. are simulated indirectly).

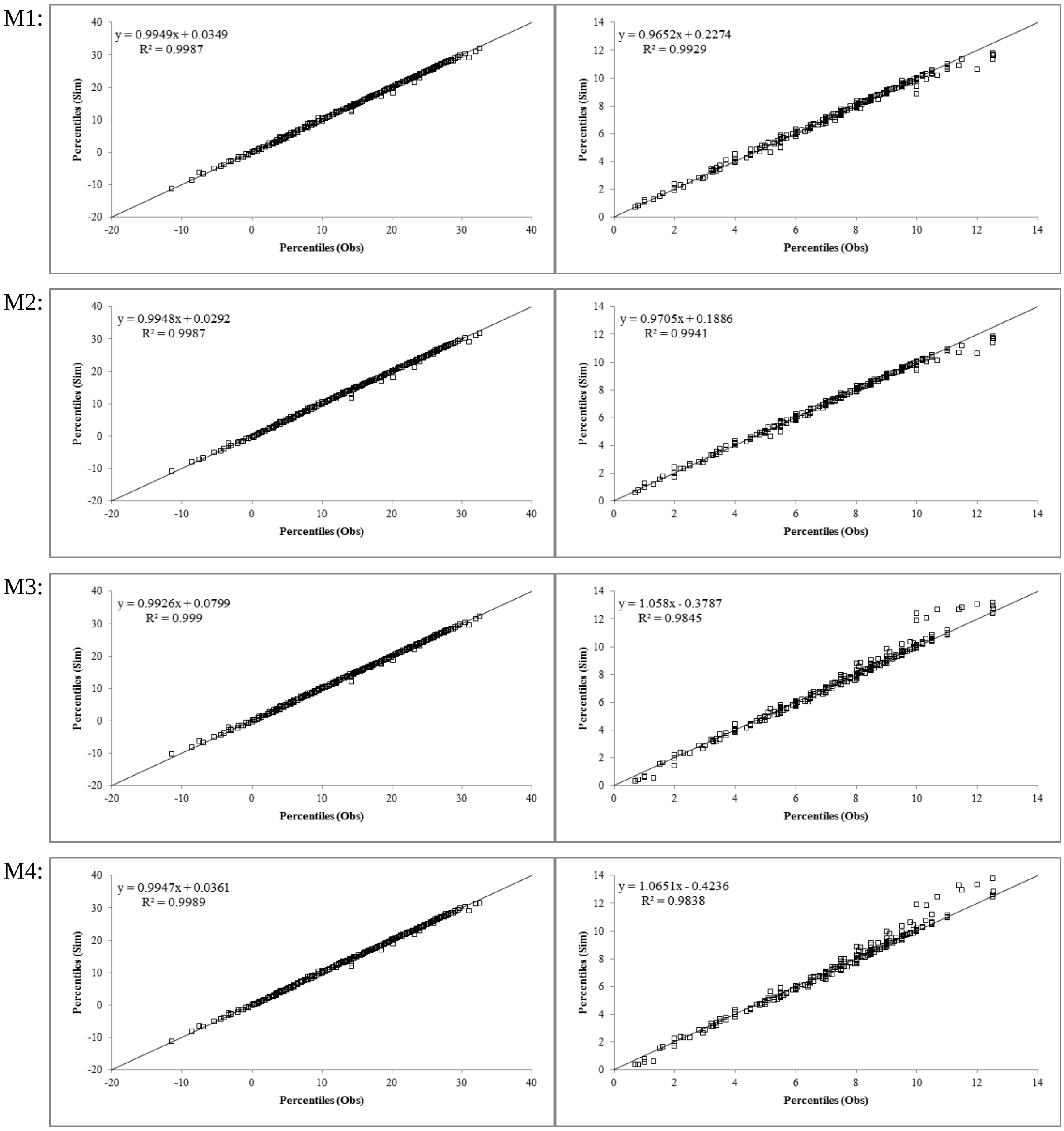
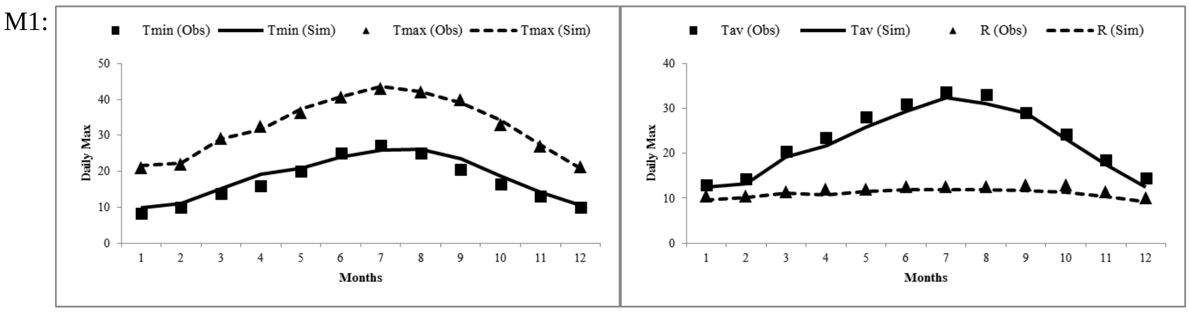
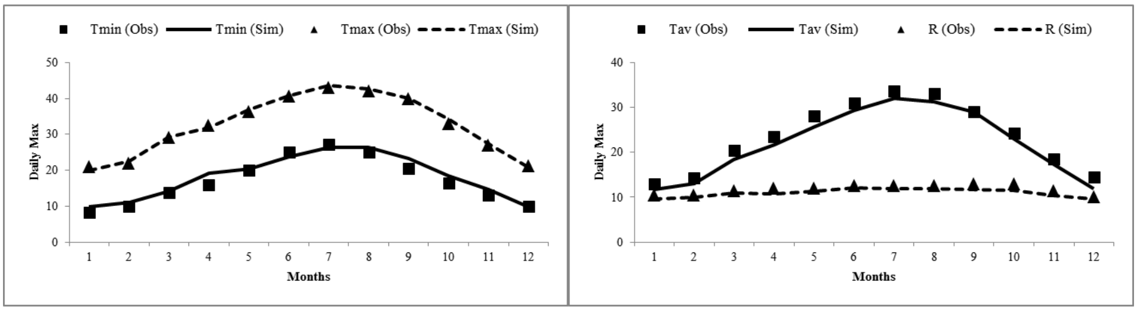


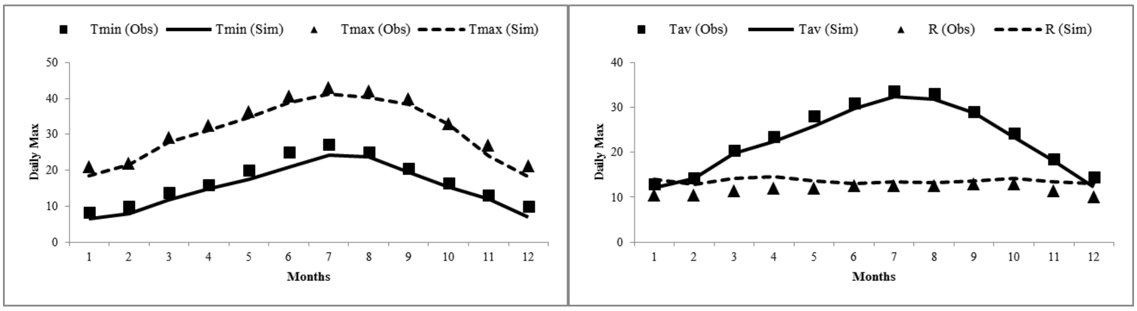
Figure 3. The percentiles (left: Tav, right: R).



M2:



M3:



M4:

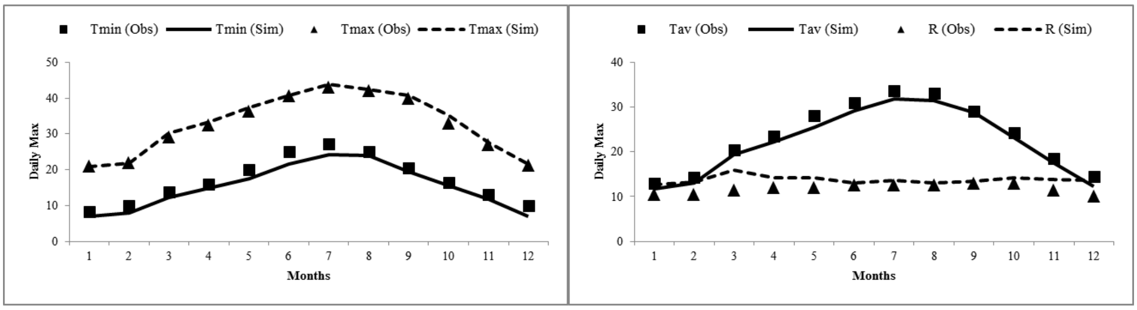
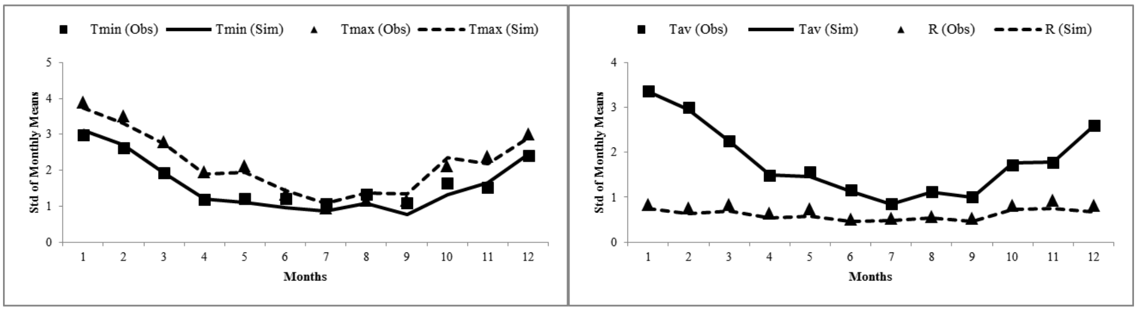
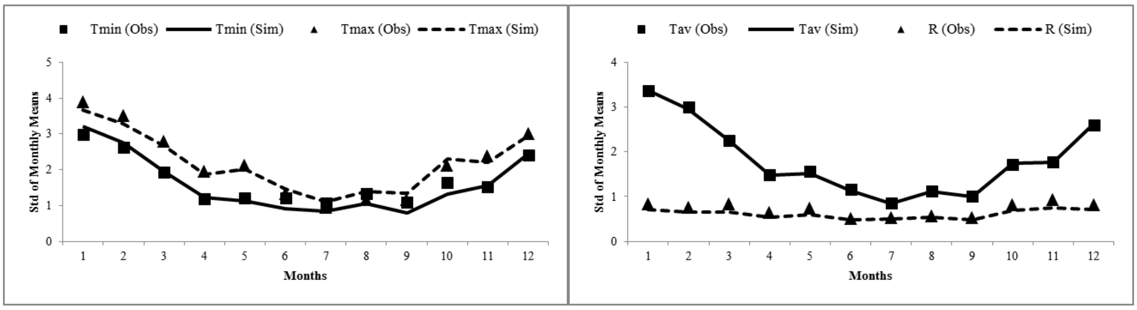


Figure 4. The monthly maximum values.

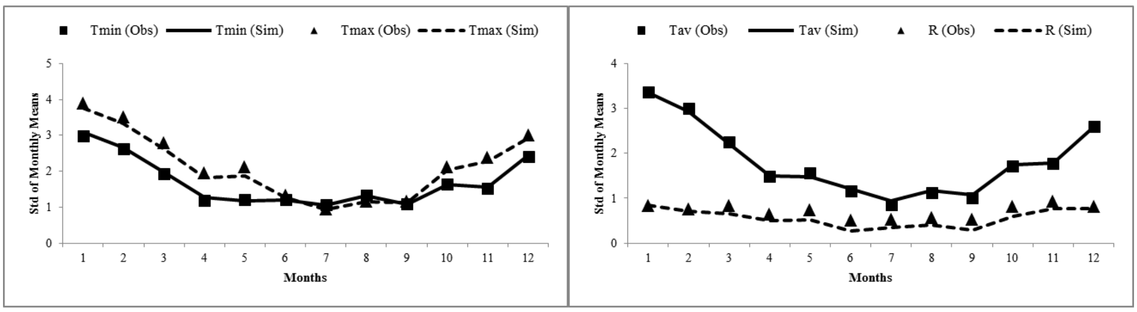
M1:



M2:



M3:



M4:

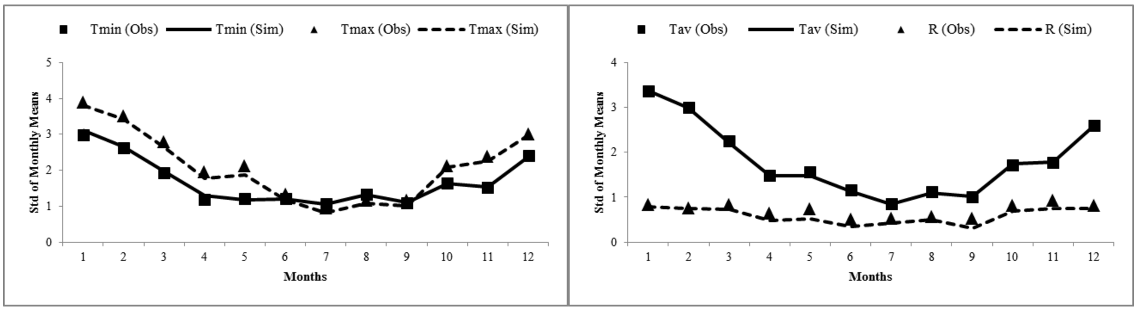
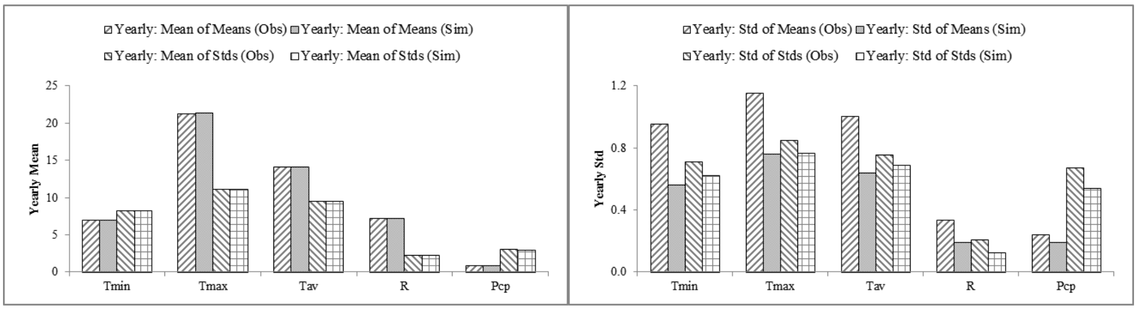


Figure 5- The interannual STD values of monthly means.

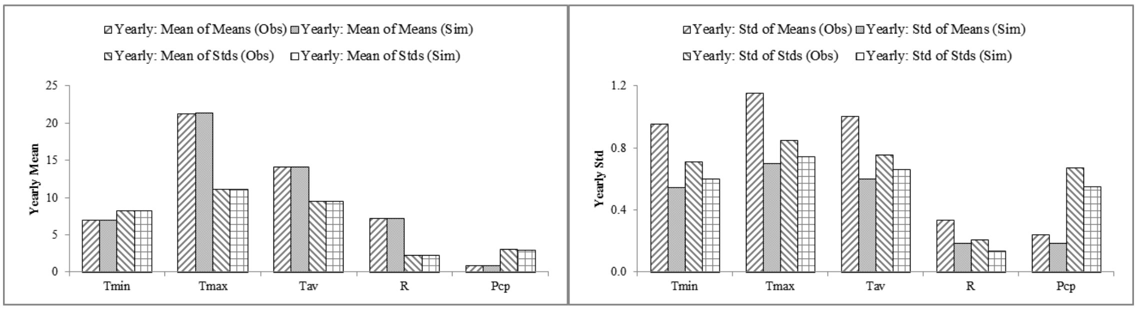
Temperature: Annual Statistics

Figure 6 shows the yearly mean and interannual STD of the annual mean and STD values for all variables. It can be seen that all algorithms performed well in relation to the yearly mean values, even for precipitation. Although all of them underestimated the interannual STD values and this issue happened because of the nature of the WG model and was reported in many studies (see the references in the Introduction). In relation to the interannual STD values, M1 outperformed the other algorithms.

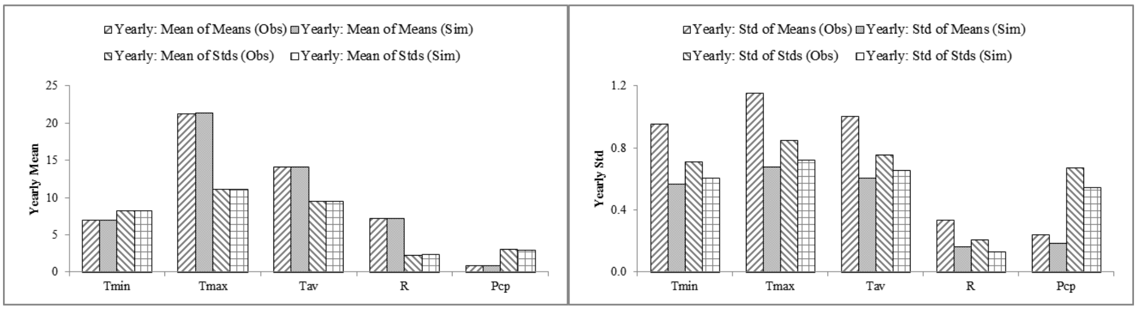
M1:



M2:



M3:



M4:

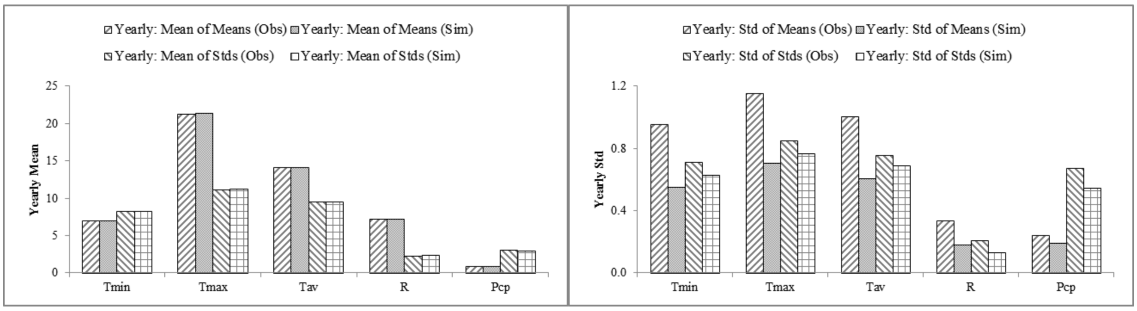


Figure 6- The mean and interannual STD of the annual mean and STD values.

Temperature: Autocorrelations

Figure 7 shows the daily autocorrelation coefficients for all variables. M1 and M2, algorithms which simulated the daily *R* values directly, simulated the autocorrelation coefficients of *R* more accurate. This issue happened because the WG model presumes a strong autocorrelation structure between variables. M3 and M4 algorithms performed very well in relation to *Tmin*, *Tmax* and *Tav* and performed acceptable in relation to *R*, although both underestimated the autocorrelation coefficients of *R*.

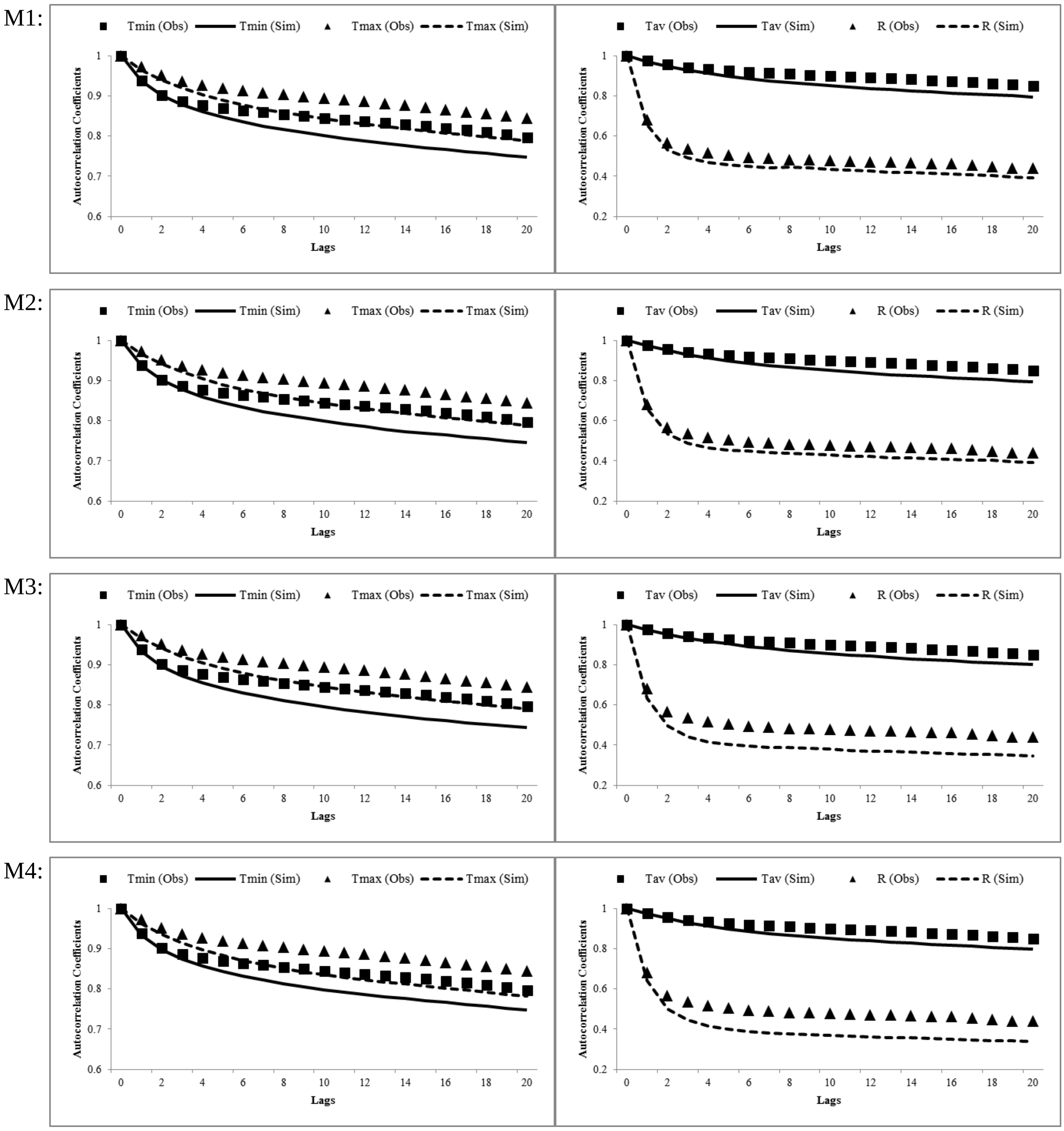


Figure 7- The daily autocorrelation coefficients.

Temperature: Cross-Correlations

Figure 8 shows the cross-correlation coefficients between *Tmin* and *Tav* and between *Tmin* and *R*. M2 algorithm overestimated the cross-correlation coefficients of *R* for the first 4 lags, but performed well in simulating the coefficients of *Tav*. Similar to the autocorrelation coefficients, M3 and M4 outperformed the other algorithms for all variables, specifically *Tmin*, *Tmax* and *Tav*.

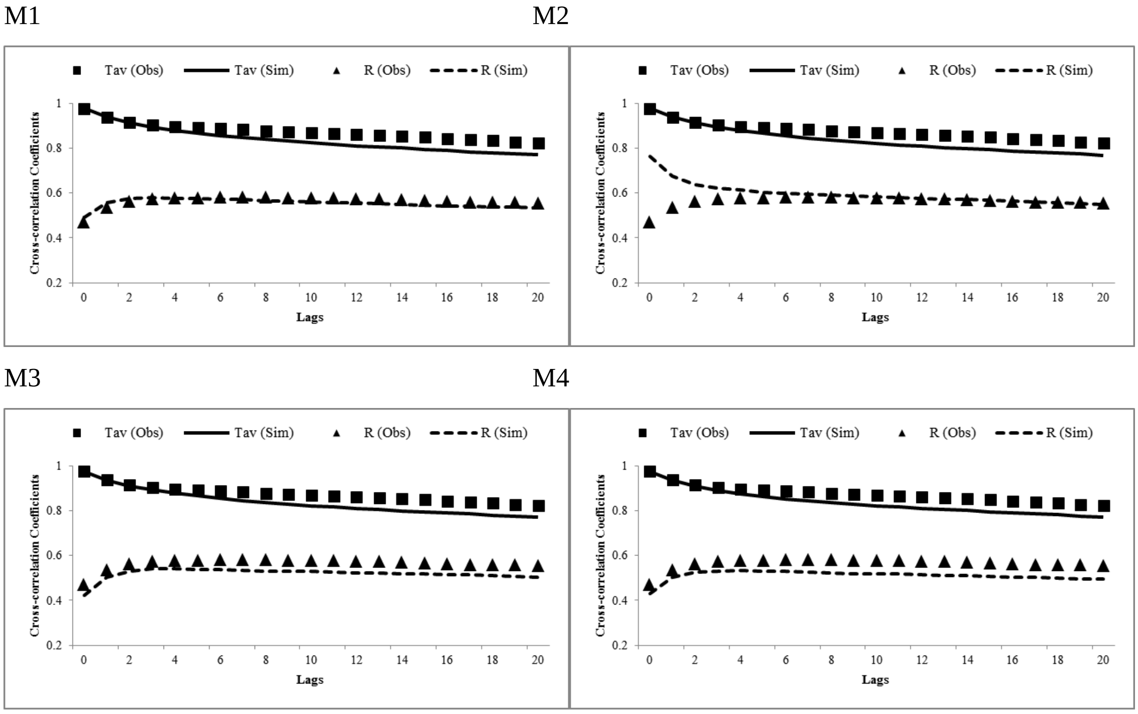


Figure 8- The daily cross-correlation coefficients between Tmin and other variables.

Temperature: Summary

Table 2 summarizes the performance of studied algorithms (XErr values) in relation to the monthly and interannual indices. It can be seen that M1 and M2 performed better in simulating the daily *R* values because this variable was simulated directly in these two algorithms. But the simulations of *Tmin* and *Tmax* indices had more deficiencies in comparison with the other algorithms. *Tav* was simulated well by all the algorithms. M3 and M4 algorithms outperformed the other algorithms in relation to *Tmin* and *Tmax*, although the differences were not considerable. As to the monthly minimum and maximum values, all algorithms performed better in simulating the primary variables (i.e. variables that are simulated directly). M1 and M2 had lower control on these extreme values of *Tmin* and *Tmax*, while the same was applicable to M3 and M4 in relation to *Tav* and *R*. Also, there were slight differences in using log- or square-root transformed *R* values while simulating with the WG model, while the differences between these two methods is considerable as to the simulation of cross-correlation coefficients of daily R values and Tmin. Moreover, the values in Table 2 show that the WG model performed better in dry days, although the higher XErr values of the wet days could because of less number of wet days in most calendar months in Qazvin station.

Table 2- Summary of the model performance (XErr values).

	M1					**M2**			
	Tmin	**Tmax**	**Tav**	**R**		**Tmin**	**Tmax**	**Tav**	**R**
Monthly: Mean	0.4%	0.2%	0.2%	0.3%		0.3%	0.2%	0.2%	0.4%
Monthly: Mean (Dry Days)	0.3%	0.3%	0.3%	0.3%		0.3%	0.3%	0.3%	0.3%
Monthly: Mean (Wet Days)	1.7%	1.1%	1.3%	1.2%		1.4%	1.3%	1.3%	1.4%
Monthly: Std	2.1%	1.5%	0.4%	2.4%		1.8%	1.1%	0.5%	1.4%
Monthly: Std (Dry Days)	3.3%	2.9%	0.7%	3.5%		2.8%	2.7%	0.6%	1.2%
Monthly: Std (Wet Days)	10.1%	6.7%	3.3%	4.4%		11.3%	5.8%	3.2%	5.6%
Monthly: Min	10.6%	12.9%	5.2%	22.2%		10.4%	19.2%	6.7%	13.0%
Monthly: Max	9.5%	1.8%	5.9%	7.2%		9.0%	1.8%	7.0%	7.1%
Monthly: Percentiles	3.5%	1.4%	1.8%	2.4%		3.5%	1.3%	1.9%	2.2%
Interannual: Mean of Means	0.3%	0.2%	0.2%	0.4%		0.3%	0.2%	0.2%	0.4%
Interannual: Std of Means	10.3%	7.2%	1.6%	15.0%		10.8%	7.4%	1.3%	15.0%
Interannual: Mean of Stds	1.6%	2.3%	0.7%	1.9%		1.6%	1.9%	0.8%	1.4%
Lag1-Correlations: Daily	7.9%					7.1%			
Lag1-Correlations: Monthly	2.4%					3.1%			
Average	**4.5%**	**3.2%**	**1.8%**	**5.1%**		**4.5%**	**3.6%**	**2.0%**	**4.1%**
	M3					**M4**			
	Tmin	**Tmax**	**Tav**	**R**		**Tmin**	**Tmax**	**Tav**	**R**
Monthly: Mean	0.4%	0.2%	0.2%	0.4%		0.4%	0.2%	0.1%	0.4%
Monthly: Mean (Dry Days)	0.3%	0.3%	0.3%	0.2%		0.3%	0.3%	0.3%	0.2%

Monthly: Mean (Wet Days)	1.8%	1.4%	1.4%	1.6%		1.3%	1.3%	1.2%	1.5%
Monthly: Std	0.6%	0.9%	2.4%	7.6%		0.6%	3.2%	0.5%	9.1%
Monthly: Std (Dry Days)	0.5%	0.7%	2.4%	13.2%		0.5%	5.3%	0.6%	17.0%
Monthly: Std (Wet Days)	2.5%	3.4%	3.2%	11.1%		3.5%	4.6%	3.1%	8.9%
Monthly: Min	5.2%	7.2%	8.1%	30.1%		6.0%	20.4%	5.3%	37.7%
Monthly: Max	12.2%	5.5%	4.7%	16.3%		11.3%	2.6%	6.3%	18.2%
Monthly: Percentiles	4.1%	1.5%	1.7%	3.8%		4.0%	1.4%	1.8%	4.1%
Interannual: Mean of Means	0.4%	0.2%	0.2%	0.4%		0.4%	0.2%	0.1%	0.4%
Interannual: Std of Means	2.3%	5.2%	2.7%	22.8%		2.5%	5.8%	1.4%	17.9%
Interannual: Mean of Stds	0.6%	1.4%	3.5%	12.0%		0.7%	6.5%	0.6%	13.4%
Lag1-Correlations: Daily	9.1%					8.0%			
Lag1-Correlations: Monthly	2.8%					2.8%			
Average	**2.6%**	**2.3%**	**2.6%**	**10.0%**		**2.6%**	**4.3%**	**1.8%**	**10.7%**

Conclusions

In this study, four different algorithms were assessed for daily temperature in combination with a well-tested weather generator. Two algorithms simulated the daily *Tav* and *R* values directly and *Tmin* and *Tmax* indirectly. The third algorithm simulated *Tmin* and *Tmax* and the fourth algorithm simulated *Tmin* and *Tav* directly and the other variables indirectly. The results showed that each algorithm could perform better in simulating the primary variables (i.e. the variables which are simulated directly). This issue was more considerable in relation to the daily *R* values. M1, M3 and M4 accurately simulated the auto- and cross-correlation coefficients of this variable because of the assumption of a strong autocorrelation structure between primary variables in the WG model. Meanwhile, M2 algorithm overestimated the cross-correlation coefficients of *R* for the first 4 lags. Altogether, M3 and M4 outperformed the other algorithms in relation to most studied indices.

This study showed the importance of choosing the best temperature generation algorithm according to the requirements. If the simulation of daily *Tmin* and *Tmax* is important and there is no need for exact simulation of daily temperature ranges (*R*), the algorithms similar to M3 and M4 can be used, while if the simulation of *R* is more important, it must be considered as one of the primary variables and simulated directly using algorithms similar to M1 and M2. The authors believe that the former case is more relevant while WG models are to be combined with crop growth simulation models because there are chances to obtain very low or very high daily temperature values while using algorithms similar to M1 and M2. This issue is of great importance specially while using crop simulation models. Since there can be any exact prediction about the performance of crop simulation models in combination of these algorithms, the issue must be assessed in future studies.

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