CMWSim: Development and evaluation of probability-based weather generating software for crop growth simulation

Article *in* Italian Journal of Agrometeorology · December 2014

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CMWSim: development and evaluation of probability-based weather generating software for crop growth simulation

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Abstract: *Daily weather records often play an important role in applications of crop growth simulation models. Weather generating software is essentially important when evaluating long term time series to generate daily weather records. CMWSim is stochastic weather generating software we developed as a sub model of the MAIZESim maize growth simulation model and it generates daily precipitation, maximum and minimum temperature. The design of the CMWSim was based on a probabilistic simulation approach which adapted from the Markov chain analysis. CMWSim simulates (I) the precipitation occurrence by using transitional probability matrices of first-order two-state Markov chain, (II) the precipitation amounts by using a two-parameter gamma distribution and (III) the temperature values (maximum and minimum) by using a first-order auto-regressive model with a conditional scheme. The system is implemented as a user-friendly Windows-based software program. Simulated data are statistically analyzed and compared with observed data to evaluate the system. The results show that all comparisons are significant and precipitation patterns are well fitted with observed patterns. Simulated precipitation was slightly over-estimated at higher intensity periods (July - September), but was statistically acceptable. Maximum and minimum temperatures are also well simulated by the model and there were no misleading results. CMWSim generates weather records in acceptable significance to be used as inputs of crop growth modelling. Since this development completely used the object oriented programming concept (reusable package), it could also be able to use (integrate) with any other decision support tool which uses weather records.*
Keywords: *weather simulation software, Markov-chain, gamma distribution, precipitation.*

Riassunto: *I dati meteo giornalieri hanno frequentemente un importante ruolo nell'applicazione di modelli di simulazione della crescita delle colture. I software per la generazione dei dati meteo sono infatti essenziali nella fase di valutazione delle serie temporali a lungo termine. CMWSim è un software stocastico di generazione dati meteo, sviluppato come sub-modello di simulazione da MAIZESim per la crescita del mais. CMWSim è basato su un approccio riadattato di simulazione probabilistica che si basa sulle catene di Markov, generando precipitazioni giornaliere, temperatura massima e minima. CMWSim simula (I) il verificarsi precipitazioni utilizzando matrici di probabilità transizionale di primo ordine a due- stati della catena di Markov, (II) i valori delle precipitazioni utilizzando una distribuzione gamma a due parametri e (III) i valori di temperatura (massima e minima) utilizzando un modello auto-regressivo di primo ordine con schema condizionale. Il sistema è stato implementato con un software user-friendly per Windows. I dati simulati sono stati analizzati con tecniche statistiche e confrontati con i dati osservati per valutare il sistema. I risultati mostrano che tutti i valori confrontati sono significativi e che il modello di precipitazione è ben correlato con i valori osservati. La precipitazione simulata è risultata essere leggermente sovrastimata nei periodi ad intensità più elevate (luglio-settembre) ma è risultata comunque statisticamente accettabile. I valori delle temperature massime e minime simulate dal modello confrontate con i valori reali sono coerenti e non ci sono stati risultati fuorvianti. CMWSim genera record meteo con significatività accettabile per essere utilizzati come input per modelli di crescita delle colture. Poiché questa implementazione è basata completamente sul* object oriented programming *(pacchetto riutilizzabile), l'implementazione potrebbe anche essere applicata (integrata) a qualsiasi altro strumento di supporto decisionale che utilizza i record meteorologici.*
Parole chiave: *generatore di dati meteo, catena di Markov-chain, distribuzione gamma, precipitazioni.*

1. INTRODUCTION

Weather often plays an important role in applications of crop growth simulation models since the uncertainty and variations of weather occurrences directly affect the crop yield. This environment may create a risk in production of a particular crop. Numerous studies on the sensitivity of crop simulation models to weather changes have reported that

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Received 5 February 2014, accepted 31 May 2014.

weather variability has significantly affected crop growth and finally the yield (Jones *et al.*, 2003; Hansen, 2005). Hansen (2005) has explained that crop growth responses cannot accurately be estimated using historical weather averages, but crops respond to the interactions between daily sequences of weather and other abiotic factors such as soil, water and nutrient balance. The reliable seasonal weather forecasting at the beginning of the cropping season is a best solution to accurately estimate the production of a particular crop (Jones *et al.,* 2000; Shin *et al.*, 2009). Therefore, one of the most important requirements is to generate weather records on daily basis matching the statistical characteristics as much as similar to the actual records in particular location. In this regard, weather generating software programs (weather generators) become an essential tool in generating weather records such as precipitation (occurrence and amount), temperature (minimum and maximum), wind speed and solar radiation, etc. (Bruhn *et al.*, 1980; Richardson, 1981; Chen *et al.*, 2012).

Numerous weather generators which are developed in hydrology and agricultural systems can be found in Richardson and Wrights (1984), Danuso (2002), Baigorria and Jones (2010) and Chen *et al.*, (2012). Most generators, especially in hydrology, generate only daily precipitation (Katz RW, 1977; Geng *et al.*, 1986; Sharma and Singh, 2010). Although cited literature shows that WGEN (Richardson and Wright; 1984) is the most frequently used and referred weather generator, some other models such as LARS-WG more closely matched to observed data than WGEN (Semenov, 1998). Selection of suitable statistical models to fit the distribution of weather variables, relationship between weather variables and temporal variability of the time series are important characteristics in development of weather generating software (Dubrovsky *et al.*, 2000). Platform independent GUI-based user-friendly weather generators are useful tools for ecological modelers as they are object-oriented and reusable components are included. CLIMA is a component-based weather generator which is designed by Donatelli *et al.*, (2005). It includes components for generating most relevant weather variables such as precipitation, air temperature, solar radiation, vapor pressure deficit, wind speed and evapotranspiration. However these all generators are independent and not integrated to a certain growth model or specific to a certain crop.

The proposed model, CMWSim was specifically designed as a sub model of a maize growth simulation model (MAIZESim) which is user-friendly WINDOWS based software. Major objective of the CMWSim was to generate minimum and maximum temperatures and precipitation in acceptable significance to be used as inputs of the MAIZESim. The design of the CMWSim was based on a probabilistic simulation approach which adapted from the Markov chain analysis. CMWSim simulates the precipitation occurrence using transitional probability matrices of first-order two-state Markov chain, and the precipitation amounts using a two-parameter gamma distribution. A first-order auto-regressive model is used to simulate maximum and minimum temperature with a conditional scheme. Some other theories used in the model are adapted from published literature with some modifications. The most important feature of the CMWSim is that it is automatically run in the same time when MAIZESim is run, and consequently the growth model doesn't require additional weather inputs. This paper presents the design and implementation technologies of CMWSim and evaluation results.

2. MATERIALS AND METHODS

The CMWSim is implemented using object oriented programming language, Microsoft Visual Basic® on .NET platform. The CMWSim generates daily time series of precipitation, maximum temperature and minimum temperature. The system includes two sub models; precipitation model (PMod) and temperature model (TMod). Each sub models includes algorithms for calculations. PMod uses the first-order two-state Markov-chain for calculation of precipitation occurrences and a two-parameter gamma distribution for calculation of precipitation amount. It also includes an algorithm for estimating model parameters based on the iterative approximation method proposed by Thom (1958) for maximum likelihood estimates. TMod uses first-order auto-regressive model for calculating temperatures and it also includes a conditional scheme to correct misleading temperature values. The basic organizational diagram of the CMWSim is shown in Fig 1. Weather data were obtained from National Climatic Data Center available in http://www.ncdc.noaa.gov for the period of 1951-2008, for the station of Xi'an, China. Data included daily rainfall (mmd^{-1}), maximum air temperature (°C) and minimum air temperature (°C).

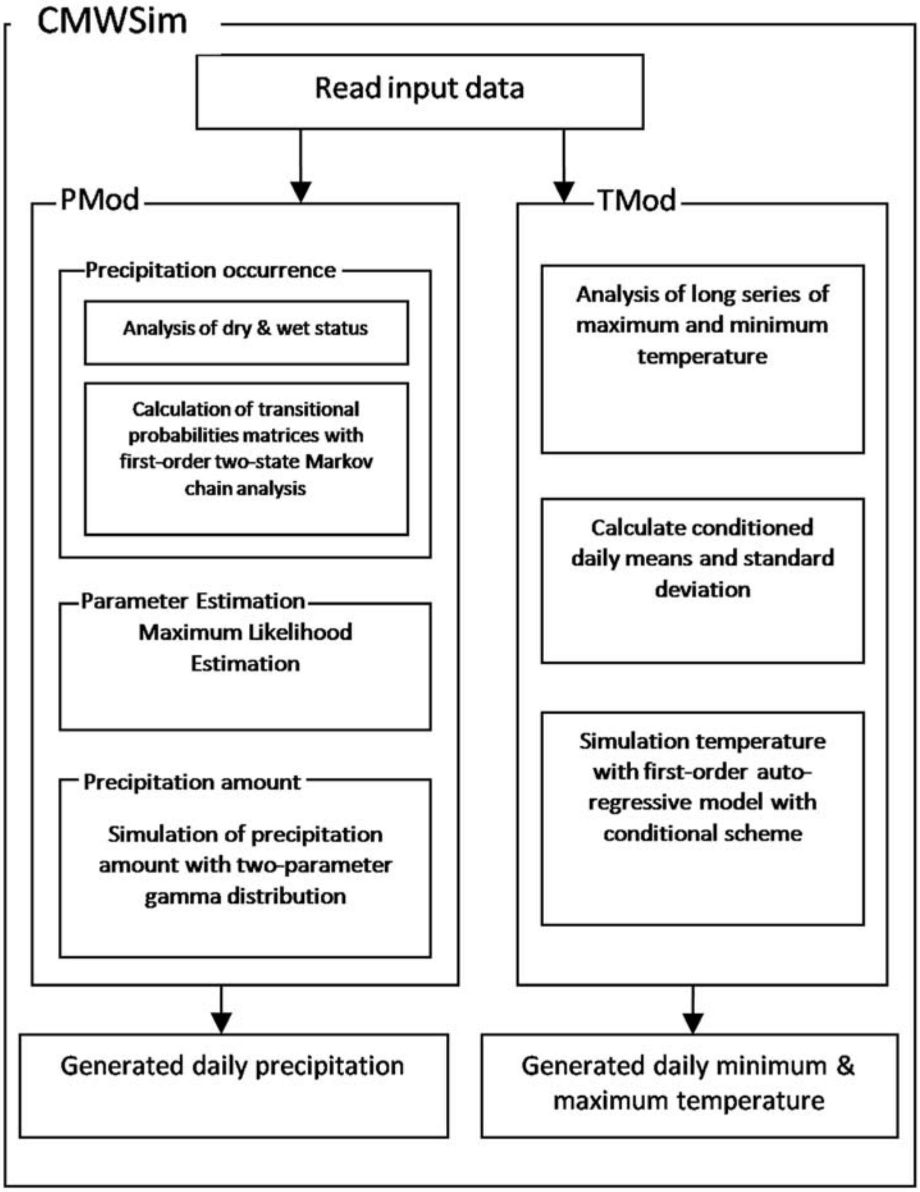

Fig. 1 - CMWSim basic organizational diagram.
Fig. 1 - Diagramma semplificato della struttura CMWSim.

2.1 Precipitation Model (PMod)

2.1.1 Precipitation occurrence

CMWSim simulates precipitation occurrence by using first-order two-state Markov chain analysis. First-order two-state Markov chain process is the simplest and most widely used model for simulating occurrence of precipitation. Numerous successful applications which use first-order two-state Markov chain can be found in Bruhn *et al.*, (1980), Richardson (1981) and Chen *et al.*, (2010). Geng (1986) and Chen *et al.*, (2012) pointed out that, "the first-order Markov chain is generally recognized as a simple and effective description of the rainfall occurrence". Wilks (1999) has also reported that the first-order model simulates the distribution of wet spells as well as higher-order models.

The two states for the Markov model were used as wet and dry. A variable for the threshold amount is defined to obtain the wet state. If the threshold or larger amount of precipitation is recorded, then the state will be wet otherwise the state will be dry (the user can define the value for threshold variable). Since the Markov model is a time ordered probabilistic process, the rainfall characteristics can be transformed from one state to another state according to the rule which is determined by the current state only, and can be presented by a transition probability matrix. Transitional probabilities are defined as,

$P_{00} = P(D/D)$ (the probability of being a dry day subsequent to a dry day)

$P_{01} = P(W/D)$ (the probability of being a wet day subsequent to a dry day)

$P_{10} = P(D/W)$ (the probability of being a dry day subsequent to a wet day)

$P_{11} = P(W/W)$ (the probability of being a wet day subsequent to a wet day)

Analyzing the threshold value, PMod produces a state vector of discrete state series (X_t) with zeros and ones according to

$$X_t = \begin{cases} 0, & \text{if day is dry} \\ 1, & \text{if day is wet} \end{cases}$$

where, $t = 1, 2, 3, \dots$

Then according to the first-order Markov chain theory, the transitional probabilities are defined as

$$Pr_{ij} = Pr\{X_t = j | X_{t-1} = i\} \qquad (1)$$

The theory explains that the state i of given day $t\text{-}1$ decided the transition probability of day t in state j. These probabilities, Pr_{ij}, are called as single-step transition probabilities. Probabilities are calculated within two week periods (14 days), and it is assumed that the probabilities are independent of t within any particular two week period (Larsen and Pense, 1981). Then,

$$Pr_{ij}^{(n14)} = Pr\{X_t = j | X_{t-1} = i\} \qquad (2)$$

where, $n14 = 1, 2, \dots, 26$

Then CMWSim estimates the probability vector which includes the elements of $Pr_{ij}^{(n14)}$. Then the elements of $Pr_{ij}^{(n14)}$ (P_{00}, P_{01}, P_{10} and P_{11}) are calculated as,

$$Pr_{ij}^{(n14)} = \frac{\sum_{t=1}^{N_{n14}} (f_{tij})}{N_{n14}} \qquad (3)$$

where, N_{n14} = number of relevant days (total wet or total dry) in $n14$

$i = 0,1$ and $j = 0, 1$

2.1.2 Precipitation amount

After estimating the probability vector of the occurrence, precipitation amounts should be calculated. PMod uses the two-parameter gamma distribution to simulate amounts of precipitation for predicted wet days. We used the gamma distribution because it has been widely accepted in published literatures (Bruhn *et al.*, 1980; Larsen and Pense, 1981; Richardson, 1984; Chen *et al.*, 2010), and it performs better than exponential distribution in generating precipitation (Richardson, 1981; Chen *et al.*, 2012). More details and reasons for accepting the gamma distribution can be found in Husak (2007). The probability density function of the two-parameter gamma distribution can be expressed as,

$$f(x) = \frac{x^{\alpha-1} exp^{(-x/\beta)}}{\beta^{\alpha}\Gamma(\alpha)}, \quad x, \alpha, \beta > 0 \qquad (4)$$

where, α and β are shape and scale distribution parameters respectively. $\Gamma(\alpha)$ is the gamma function and x is the precipitation amount. Parameters (α, β) were estimated using maximum likelihood estimates (Thom, 1958). Transitional probabilities (P_{11} or P_{01}) and uniform random numbers between 0 and 1 produced by the computer are used to predict the wet days. The first day of the predicted wet days is considered as a dry day. The random number should be compared with P_{01} of this two week period. If random number is higher than P_{01}, the following day keeps no rainfall and considered as dry day. Otherwise the following day considered as a wet day. Then the precipitation amounts for predicted wet days were sampled with gamma parameters and uniform random numbers.

2.1.3 Parameter estimation

Parameter estimation is critically important when fitting data with distributions because the behavior of the distribution is characterized by the distribution parameters. Different theories have been applied in estimating the distribution parameters. Maximum likelihood estimates is mostly accepted for two-parameter gamma distribution. Polynomial approximation of maximum likelihood proposed by Greenwood and Durand (1960) was applied in some applications in hydrology and agricultural systems modelling. Examples can be found in Larsen and Pense (1981), Geng (1986) and Baigorria and Jones (2010). But some authors have pointed out that the Greenwood and Durand method has some limitations and it is quite unstable when shape parameter (α) of the gamma distribution is close to zero (Johnson and Kotz, 1970; Dang and Weerakkody, 2000). However, some other authors have used methods of moments as they show closer results for their studies (Danuso, 2002; Barkotulla, 2010). In our study, we used an iterative approximation method proposed by Thom (1958) for maximum likelihood estimates since it is better than the moment method (Thom, 1958; Shenton and Bowman, 1970).

Thom (1958) has explained in detail how to derive the shape parameter (α) and the scale parameter (β) of the gamma distribution (Eq. (4)). For that Thom obtained the maximum likelihood equation from the gamma distribution function as,

$$\alpha = \frac{1 + \sqrt{1 + 4y/3}}{4y} \tag{5}$$

where α is the shape parameter and

$$y = ln\,\frac{\bar{x}}{\hat{x}}$$

where $\hat{x}$ = geometric mean and $\bar{x}$ = arithmetic mean of the sample precipitation data
then y becomes,

$$y = ln\,\frac{\sum_{i=1}^{n} x_i/n}{\left(\prod_{i=1}^{n} x_i\right)^{1/n}} \tag{6}$$

where n = number of non-zero precipitation days in a month, x_i = observed non-zero precipitation and i = 1, 2, …, n.
According to Thom's explanation the scale parameter (β) can be obtained from the arithmetic mean ($\bar{x}$) and shape parameter (α) as,

$$\beta = \frac{\bar{x}}{\alpha} \tag{7}$$

2.2. Temperature model (TMod)

Most of the weather generators have included a temperature model to simulate temperature with other weather variables (Richardson, 1981; Danuso, 2002; Golubyatnikov, 2004; Chen, 2012; Shahin, 2013). However Richardson (1981) and Chen *et al.*, (2011) pointed out that the attention to simulation of temperature is comparatively less than the precipitation and therefore different temperature models and correction tools are less documented. Most of the existing models have applied the first-order linear auto-regressive model to simulate the temperature values though they have problems with underestimation of monthly and annual variability (Dubrovsky *et al.*, 2004). Temperature model (TMod) of the CMWSim simulates daily maximum and minimum temperatures using historical temperature data. We also used the first-order linear auto-regressive model including a conditional scheme adapted from Chen *et al.*, (2012), and scheme can avoid the misleading maximum temperature simulations.
Residual elements were calculated from the observed temperature values by subtracting the mean and dividing by the standard deviation as the first step. At this stage, the temperature values, maximum and minimum, were considered separately for the dry and wet days, and the dry or wet state is same as we obtained to generate precipitation in PMod. Then the residual series are generated, followed by the Richardson (1981) and Chen *et al.*, (2012), using

$$\chi_i(j) = \boldsymbol{A}\chi_{i-1}(j) + \boldsymbol{B}\varepsilon_i(j) \tag{8}$$

where, $X_i(j)$ is a (2 x 1) matrix of the residuals of temperatures for day i, and $\Sigma_i(j)$ is another (2 x 1) matrix of normally distributed independent random components. $\boldsymbol{A}$ and $\boldsymbol{B}$ are (2 x 2) matrices of serial and cross correlation coefficients of observed residuals and are defined by

$$\boldsymbol{A} = \boldsymbol{M}_1\boldsymbol{M}_0^{-1} \tag{9}$$

$$\boldsymbol{BB}^T = \boldsymbol{M}_0 - \boldsymbol{M}_1\boldsymbol{M}_0^{-1}\boldsymbol{M}_1^T \tag{10}$$

where, $\boldsymbol{M}_0$ and $\boldsymbol{M}_1$ are lag_0 and lag_1 covariance matrices.
After calculating the correlation coefficients for the matrices, the CMWSim generates the new sequences of residuals using Eq. (8). Then daily minimum temperature (*TMin*) and maximum temperature (*TMax*) are generated by multiplying the residuals with standard deviation (σ) and adding the mean (μ). To avoid the misleading results of temperature values, we used a conditional scheme proposed by Chen *et al.*, (2012). If the standard deviation of maximum temperature is larger than or equal to the standard deviation of minimum temperature, daily temperature values are generated by equations (11) and (12).

$$T_{Min} = \mu_{Min} + \sigma_{Min} * \chi_i \tag{11}$$

$$T_{Max} = T_{Min} + (\mu_{Max} - \mu_{Min}) + + \sqrt{\sigma_{Max}^2 - \sigma_{Min}^2} * \chi_i \tag{12}$$

If the standard deviation of maximum temperature is less than that of minimum temperature, daily temperature values are generated by equations (13) and (14).

$$T_{Max} = \mu_{Max} + \sigma_{Max} * \chi_i \tag{13}$$

$$T_{Min} = T_{Max} - (\mu_{Max} - \mu_{Min}) - - \sqrt{\sigma_{Min}^2 - \sigma_{Max}^2} * \chi_i \tag{14}$$

3. RESULTS AND DISCUSSION

Data obtained from one climatological station in Xi'an, China is used to evaluate the CMWSim. The Xi'an station was selected as the verification location because the outputs of CMWSim will be used as inputs by the maize simulation model MAIZESim, and Xi'an is one of the large-scale maize growing areas in China. We used 58 years of historical weather data available in Xi'an station in order to verify the developed system accurately. The general description of the 58 years data is as follows: the annual precipitation varies from 312 mm (in 1995) to 903 mm (in 1983) and average annual precipitation for these 58 years is 572 mm. Monthly precipitation varies from 0mm (in January, February, March, November and December) to 344mm (in July). Maximum temperature varies from 42^0 C to -8^0 C and minimum temperature varies from 30^0 C to -20^0 C.

3.1 Precipitation occurrence and amount

Precipitation occurrences were generated using first-order two-state Markov chain, and the considered threshold value was 0.25 mm/day. Then precipitation amounts were generated using the two-parameter gamma distribution for wet days. Results were analyzed statistically to compare with observed values to evaluate the CMWSim program. Frequency of wet days (Tab. 1), mean monthly precipitation (Fig. 2) and standard deviation of monthly precipitation (Fig. 3) were compared and analyzed statistically with observed data in order to ensure the statistical significance of the results. Daily mean precipitation was also compared with the observed (Fig. 4). It is clear from the figures 2, 3 and 4 that, simulated data are closely fitted to observed data. The pattern and shape of precipitation distributions of simulated values are

Month	Number of wet days	
	Observed	Simulated
Jan	4	3
Feb	4	4
Mar	6	6
Apr	8	8
May	8	9
Jun	8	8
Jul	10	11
Aug	10	10
Sep	11	12
Oct	11	11
Nov	6	7
Dec	4	3

Tab. 1 - Comparison of frequency of wet days/month.
Tab. 1 - Confronto della frequenza delle irrigazioni giorni/mese.

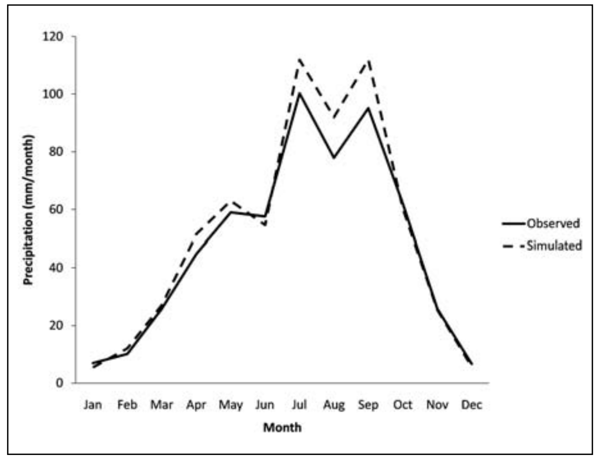

Fig. 2 - Observed and simulated monthly mean precipitation.
Fig. 2 - Precipitazioni medie mensili osservate e simulate.

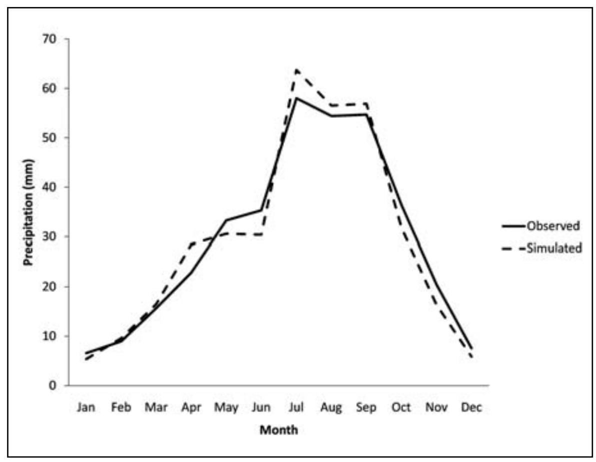

Fig. 3 - Observed and simulated monthly standard deviation of precipitation.
Fig. 3 - Deviazione standard delle precipitazioni medie mensili osservate e simulate.

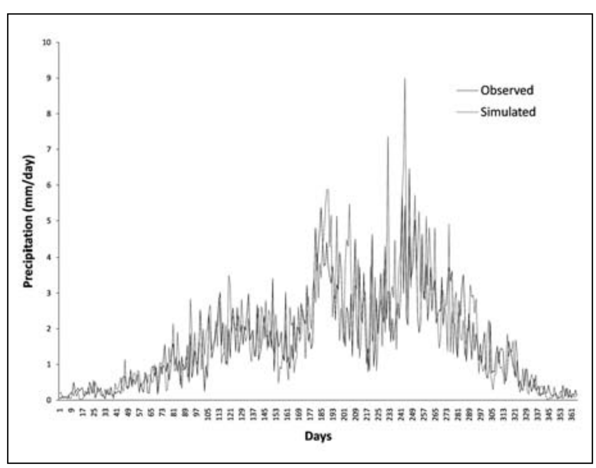

Fig. 4 - Observed and simulated daily mean precipitation.
Fig. 4 - Precipitazioni medie giornaliere osservate e simulate.

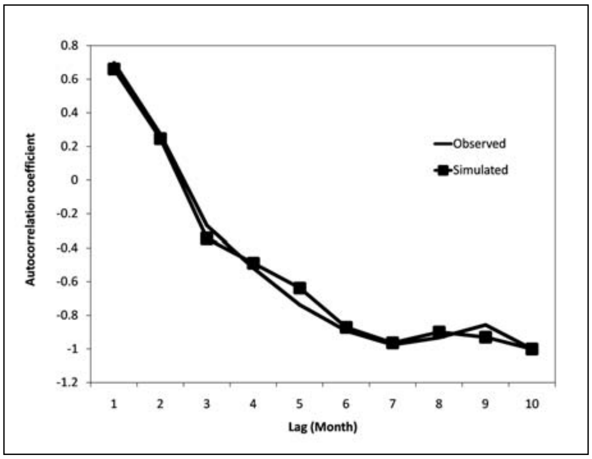

Fig. 5 - Monthly autocorrelation for observed and simulated precipitation.
Fig. 5 - Autocorrelazione mensile per le precipitazioni osservate e simulate.

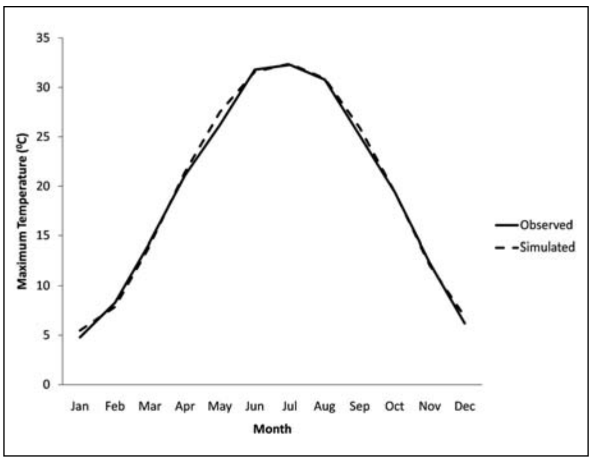

Fig. 6 - Observed and simulated mean of monthly maximum temperature.
Fig. 6 - Temperatura massima mensile osservata e simulata.

much closer to observed values in all the times. Although slightly overestimated precipitation could be observed at higher intensity periods (July - September), no significant difference was found between mean monthly precipitations with t-test at p=0.05. Autocorrelation coefficients are also best fitted (Fig. 5) in monthly average precipitation calculated for first ten months. Results reveal that first-order markov chain is best fitted to analyze frequency of wet days in Xi'an area. The two-parameter gamma distribution is acceptable especially for dry months than wet months with high intensity. However the Xi'an station is much wetter in the 3rd quarter of the year (July - September) and it could be the reason for overestimated precipitation in the wet months. This indicates that the CMWSim generally perform better when simulating precipitation for dry months than wet months.

3.2 Temperature

Maximum and minimum temperatures are simulated by CMWSim using the same wet and dry states simulated by the first-order two-state Markov chain used in PMod. The results were compared with observed mean and standard deviation of monthly temperatures (Fig. 6 - Fig. 9). Results reveal that the all time maximum and minimum temperature values are well fitted with observed values. Differences between observed and simulated mean and standard deviation of monthly

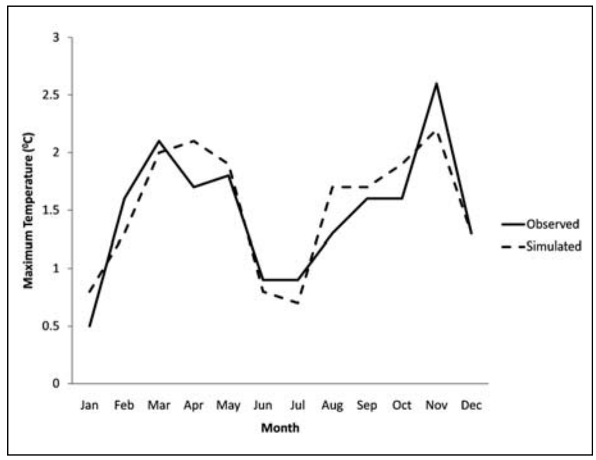

Fig. 7 - Observed and simulated standard deviation of monthly maximum temperature.
Fig. 7 - Deviazione standard osservata e simulate dei valori delle temperature massime mensili.

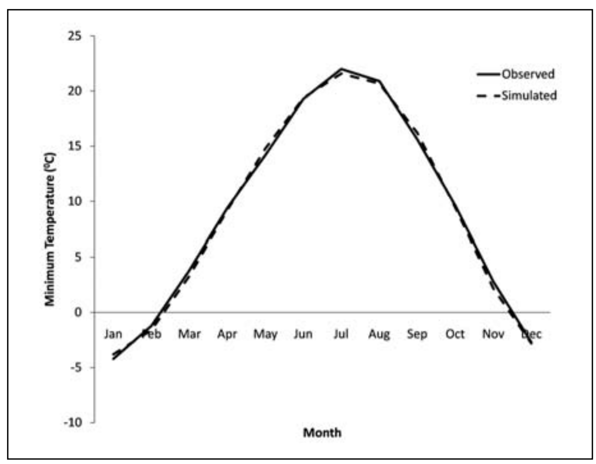

Fig. 8 - Comparison of observed and simulated mean of monthly minimum temperature.
Fig. 8 - Confronto dei valori di temperatura minima mensile osservata e simulata.

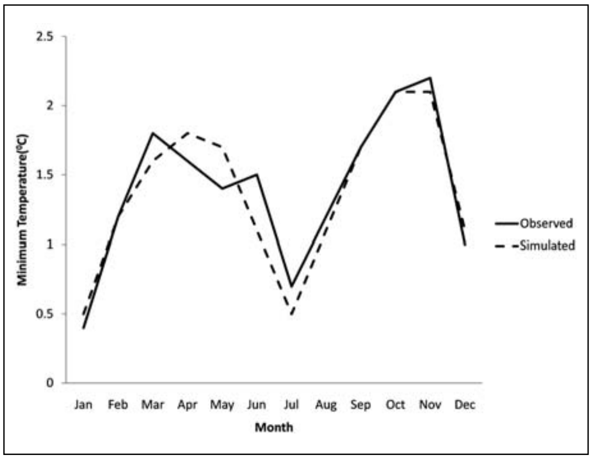

Fig. 9 - Comparison of observed and simulated standard deviation of monthly minimum temperature.
Fig. 9 - Confronto della deviazione standard osservate e simulate dei valori di temperature minime mensili.

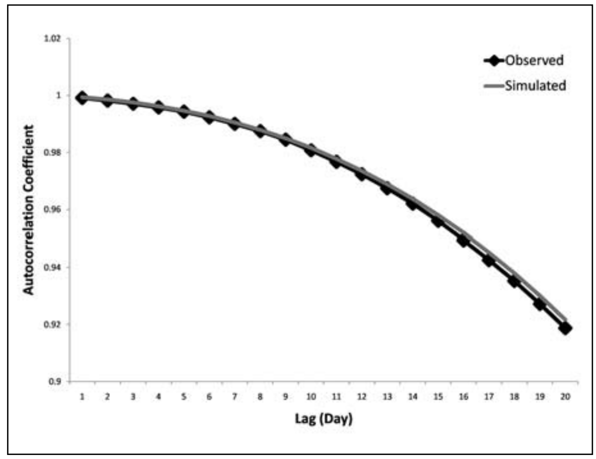

Fig. 11 - 20 days of lagged autocorrelation for observed and simulated minimum temperature.
Fig. 11 - Autocorrelazione su 20 giorni dei valori di temperature minima osservati e simulati.

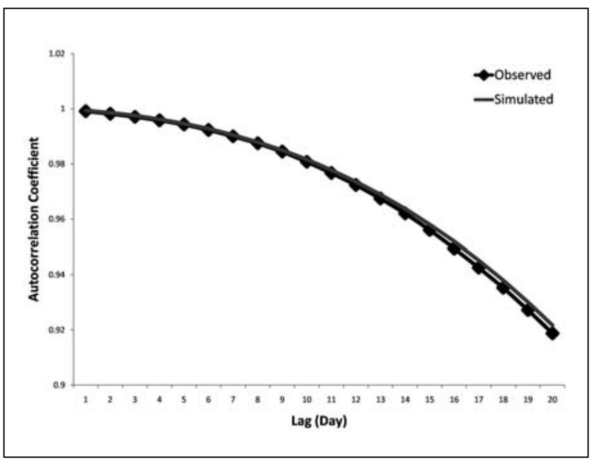

Fig. 10 - 20 days of lagged autocorrelation for observed and simulated maximum temperature.
Fig. 10 - Autocorrelazione su 20 giorni per i valori di temperature massima osservati e simulati.

temperature are less than one degree. The pattern and shape of temperature distributions of simulated and observed values are almost same in all the times, and no significant difference was found between daily temperature values with t-test at p=0.05. Autocorrelation functions computed for the CMWSim generated and observed values clearly show that the persistence of the daily temperature values is well preserved (Fig. 10 and Fig. 11) by the conditional scheme (Chen *et al.*, 2012) applied, and therefore no misleading results of minimum and maximum temperature were found. As indicated by Chen *et al.*, (2012), "the autocorrelation is a measure of the persistence of temperature trends, and is an important characteristic to reproduce", overall, the CMWSim would be a great tool for simulating precipitation and temperature values.

4. CONCLUSION

The user-friendly windows-based weather generating software (CMWSim) has been developed successfully. The simulation of precipitation occurrence and amount were successfully completed with first-order two-state Markov chain and the two-parameter gamma distribution and simulation of temperature was also successfully completed by using the first-order auto-regressive with a conditional scheme. The model was verified with the data obtained from the station where the maize field trials will be conducted since the results of this weather generator will be used as inputs by the maize growth simulation model (MAIZESim). All weather variables, precipitation, maximum and minimum temperature are well simulated by the CMWSim on daily basis. Consequently, we can conclude that the CMWSim is reliable to generate weather data as input variables for the maize simulation model, further it would be great for temperature simulation and precipitation specially for dry months even though a slightly over estimated the wet months with higher intensity. The first-order two-state Markov chain model can be used successfully to simulate precipitation as widely used by others while the two-parameter gamma distribution is well acceptable in generating precipitation amounts. Further, the first-order autoregressive model can be used to generate temperature time series, and conditional scheme proposed by Chen *et al.*, (2012) is acceptable to avoid misleading results in daily temperature simulation. Since the developed generator is only a sub model of the MAIZESim, after integrating to and completing the MAIZESim, further studies can be done in terms of evaluating the weather variability on crop growth. In addition, the software may be helpful for farmers, crop management decision makers, students and scientists as a decision making or research tool. Since the software was developed using object oriented programming technology and it is supported to add components, there is a capable of adding new components to the main model.

5. ACKNOWLEDGEMENTS

This research was supported by the National High Technology Research and Development program of China (863 program, Project number: 2013AA102304).

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