Improved conditional weather generator for extreme precipitation events

National Meteorological Administration

Aristita Busuioc

1. Introduction

Weather generators (WGs) are statistical models generating synthetic sequences of local variables that replicate their statistical attributes (such as the mean and variance) but not observed sequences of events (Buishand et al., 2004; Huth et al., 2001; Busuioc and von Storch, 2003; Kattz et al., 2003; Palutikof et al., 2002; Wilby et al., 2003). Generally, these models focus on the daily time scale, as required in many impact studies. The most used daily weather generators are based on the approach to modelling daily precipitation occurrence and usually these rely on stochastic processes via first-order autoregressive process. The Markov chain is widely used to describe the precipitation occurrence (wet/dry day or spells) and variation of precipitation amount on wet days is described by appropriate probability distributions such as exponential, gamma or mixed distribution. WGs are adapted for statistical downscaling by conditioning their parameters on large-scale atmospheric predictors. There are various ways to define the large-scale conditions such as: circulation indices (e.g. Katz et al., 2003), circulation clasification (e.g. Palutikof et al., 2002), regression models (Buishand et al., 2004; Busuioc and von Storch, 2003; Wilby et al., 2003). Katz et al. (2003) and Wilby et al. (2003) used a conditional weather generator for multi-site simulation of precipitation.

The National Meteorological Administration (NMA) contribution in the ENSEMBLES project

(RT2B) is related to the development of a conditional weather generator to generate daily precipitation time series in order to calculate various statistical parameters, including extreme precipitation indices. This model uses a first-order Markov chain combined with a statistical downscaling model (SDM). More details about this model were presented by Busuioc and von Storch (2003) where it has been tested for one station (Bucharest) at which long daily observations were available (1901-1999). The sea level pressure (SLP) has been considered as large –scale predictor. Within the ENSEMBLES project this model has been developed for more stations over the Romanian territory using various predictors. The methodology is shortly presented in Section 2. The skill of the downscaling model in estimation of precipitation distribution parameters and the skill of the conditional stochastic model in reproducing the most important statistical features of the generated precipitation time series are shown in Section 3. Conclusions are summarized in Section 4.

2. Methodology

The model presented in this report is a combination between a first-order Markov chain and a statistical downscaling model. Observational data refers to the interval 1950-1999 and they are seasonally stratified: Winter (December-February), Spring (March-May), Summer (June-August), Autumn (September-November). Precipitation occurrence is described by a two-state, first-order Markov chain. The precipitation either occurs or it does not (the two states) and the conditional probability of precipitation occurrence depends only on the occurrence on the previous day. There are two parameters describing the precipitation occurrence process: the transition probability p_{01}, the probability of a wet day following a dry day, and p_{11}, the probability of a wet day following a wet day. As a wet day, the case of daily precipitation amount > 0.1 mm is used in this study. The variation of precipitation amount on wet days is described by the gamma distribution which has two parameters: the shape parameter (k) and the scale parameter (β) (Coe and Stern, 1982; Wilks, 1992). In terms of the two distribution parameters, the mean precipitation amount (considering only wet days) is $\mu=k\beta$. In this study, μ and k are considered the gamma distribution parameters. μ is estimated as the sample mean from the observed data set and k is derived as solution of the equation,

$$\ln(k)-\psi(k)=\ln(\bar{x})-\overline{\ln(x)}$$

where $\bar{x} = [\sum_{i,t} x_i(t)]/n$, $\psi(x)$ is the first derivate of the log Gamma function and it is obtained using a computational subroutine by Amos (1983); $x(t)$ represents in our case the daily precipitation amount for wet days.

The p_{01}, p_{11} transition probabilities are estimated from the observed data set. Therefore, the stochastic model to generate daily precipitation depends on four parameters (p_{01}, p_{11}, μ and k). The four parameters were computed over the two subintervals: 1950-1974 and 1975-1999, used as calibration and validation intervals. For this report the model was fitted over the 1975-1999 period and validated over the 1950-1974. The work will continue by reversing the two intervals in order to test the model stability.

The four parameters are linked to the large-scale circulation through a linear model based on canonical correlation analysis (CCA; von Storch et al., 1993; Busuioc et al., 1999, 2001). Specific humidity (SH) and potential instability (Q) indices and SLP taken from the NCEP-NCAR reanalysis (Kalnay et al., 1996) were used as predictors (either used individually or together). The domain sizes for these predictors were selected so that the skill of the downscaling model (expressed as explained variance and correlation coefficient) linking the four precipitation distribution parameters and predictors is maximum. Therefore, the following predictor domains have been selected: SLP (5^o-50^oE and 30^o-55^oN), SH and Q (20^o-30^o E and 40^o-50^o N). The SH index is defined as the average over the levels 1000 hPa, 950 hPa, 850 hPa and 700 hPa. The Q index is defined using the methodology presented by Cacciamani et al. (1995) and more details about this are also presented by Busuioc et al. (2007).

The stochastic parameters (p_{01}, p_{11}, μ and k) are computed for every season from 90 to 92 daily precipitation amounts in every year. In this way, a time series of the parameters is obtained. Prior to the CCA the four parameters have been standardized, by subtracting the mean from the original value and by dividing with the standard deviation. The same procedure is applied for predictors when they are used in combination, otherwise only anomalies are considered. Two versions of the conditional stochastic model have been tested. The first one, presented by Busuioc and von Storch (2003), applies the CCA downscaling model for the four stochastic parameters together for each station. The second one, presented in this report, applies the CCA for each parameter at more stations that gives more spatial coherence of the results. Therefore, the CCA determines pairs of patterns of two-time-dependent variables (the large-scale predictors and spatial vector of each stochastic parameter) so that their time components are optimally correlated. Both predictands and predictors are projected onto their EOFs (Empirical Orthogonal Functions) to eliminate noise (small-scale features) and to reduce the dimension of the data. Since the time coefficients are normalized to unity, the canonical correlation patterns represent the typical strength of the signals. A subset of CCA pairs is then used in a regression model to estimate the spatial vector of each stochastic parameter from the large-scale predictors. The precipitation distribution parameters (p_{01}, p_{11}, μ, k) estimated through the various CCA models are then used in the stochastic model in order to generate daily precipitation amounts. These time series are achieved for every season in every year. Since the four parameters should satisfy some conditions ($0 \leq p_{01}, p_{11} \leq 1$ and $\mu, k > 0$) the CCA model outputs are processed by applying the reversed operation of standardization before being used in the stochastic model.

The conditional stochastic model performance is assessed in two steps: firstly, the performance of the CCA model (expressed as explained variance by reconstructed values from the total observed variance and correlation coefficient between observed and reconstructed values) in estimating the four parameters and secondly, the stochastic model performance in reproducing the observed precipitation statistical parameters: daily mean precipitation amount, daily standard deviation, maximum of daily precipitation amount, maximum duration of wet/dry intervals and frequency of precipitation exceeding some thresholds. All these parameters are calculated as the ensemble mean over 1000 model runs. 90 % confidence intervals for each precipitation statistical parameter are estimated and the capability of the conditional stochastic model to cover the corresponding observed parameters by these confidence intervals is analysed. It is known that the performance of the CCA model depends on the number of EOFs/CCAs used for model calibration (Busuioc et al., 1999, 2001).

3. Results

3.1. CCA performance in estimation of the precipitation distribution parameters

In earlier work, the CCA model performance in estimating the four parameters has been tested for 24 stations distributed over the entire Romania region but with highest density in the southern part where the downscaling results will be applied for impact study in the CECILIA project. It was found that the CCA model performance is very sensitive to the predictand's domain size and spatial density of the rainfall stations. Therefore, as part of more recent ENSEMBLES work, the model has been tested for 10 stations in southern Romania (see Figure 1), for winter, summer and autumn seasons.

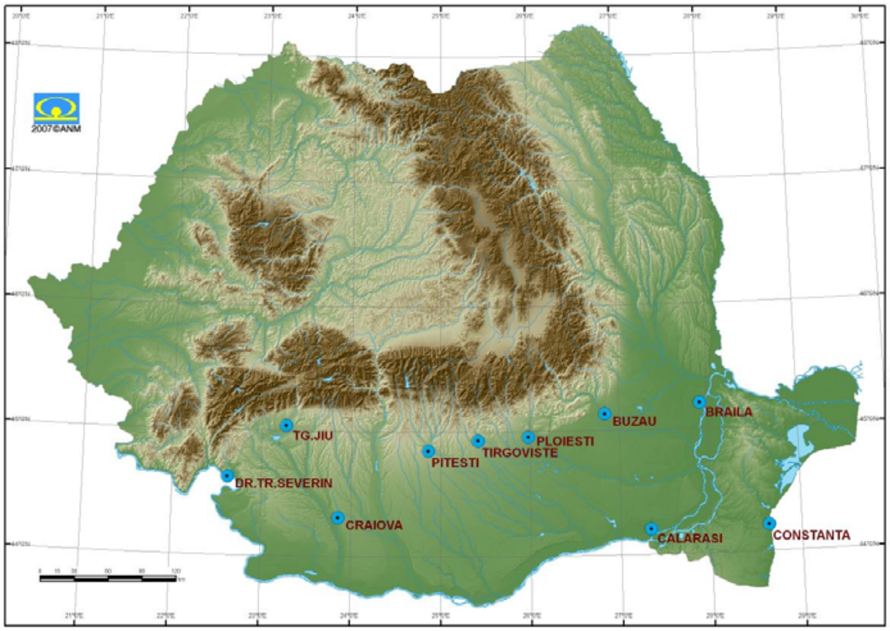


Figure 1. The location of stations used in this study.

The model skill was calculated over the independent data set 1951-1974 with the model calibrated over the interval 1975-1999. The work will continue by reversing the two intervals in order to test the model stability. It was found that the highest performance was obtained for the winter p01 parameter, using SLP as predictor. Similar results were obtained using the combination between the SLP and SH predictors. Finally, this combination was preferred since the future climate change signal is better captured by moisture predictors. The instability index improved the model skill only for a few stations in case of the p01 parameter and for almost all stations for the other winter parameters and all parameters and all stations for summer. For autumn, SLP is the best predictor for a small south-western region, SLP+SH and Q for other sub-regions, respectively, in the case of the p01 parameter. For the other three parameters, the CCA model is skilful only for some stations.

Tables 1 and 2 summarise the performance of the CCA model for winter and summer. As discussed in Section 2, the performance of the statistical downscaling model depends on the number of EOFs/CCAs. In a previous paper (Busuioc et al., 1999) the combination of EOFs and CCAs was selected so as to maximize the correlation coefficient between the spatial averages of observed and reconstructed anomalies. Obviously the SDM selected in this way for the entire country (corresponding to an optimum EOFs/CCAs combination) does not imply a high skill for all stations. Busuioc et al. (2006) proposed an alternative technique to optimize the SDM skill by selecting the SDM with the highest performance (from a SDM hierarchy obtained by using various combination of EOFs/CCAs) separately for each station rather than considering the overall performance for the entire country. This technique is also used in this study.

As can be seen in Table 1, the same EOF/CCA combination of the SLP+SH predictor was found to be most skilful for the winter p01 parameter. Similar results are obtained using SLP alone. This result shows that the p01 variability for southern Romania is controlled by the same large-scale mechanism, namely atmospheric circulation variability. The fact that the inclusion of the moisture and instability predictors does not significantly improve the CCA model performance (except for Tirgoviste station) means that the dynamical factor (advection) is more important than the thermodynamical one in the winter season. As expected, this result is in agreement with those presented by Busuioc et al. (2006) by analysing the winter total precipitation amount. For the winter p11 and μ parameters it seems that the instability index is the best predictor, while for the k parameter, SH is the best predictor, but using various EOF/CCA combinations, especially for gamma parameters (μ and k). This result shows that gamma parameter variability for the winter season is mainly controlled by regional thermodynamical factors. Lower SDM skill for these parameters could be explained by additional local factors. The combination between SLP and Q gives a significant improvement of the model skill for some south-western stations (Tg. Jiu and Craiova). As an example, Figure 2 displays the estimated and observed standardized anomalies of the four parameters at Tg. Jiu station. A very coherent evolution of the two curves for the transition probability parameters can be seen.

For summer season (Table 2), as it was expected, the dynamical factor is less important, the instability and moisture parameters controlling the variability for all precipitation distribution parameters. However, the performance of the CCA model is lower than for the winter season. The EOF/CCA combination is also less stable compared to the winter case. This result could be explained by the fact that the predictor spatial resolution is still too coarse in order to be able to pinpoint the summer convection processes affecting this region.

Table 1. Skill of the CCA model (expressed as percentage of explained variance/correlation coefficient*100) for estimation of the four parameters (p_{01}, p_{11}, μ , k) from various predictors over the subinterval 1951-1974 considered as independent data set with the model fitted over the subinterval 1974-1999. The highest skill for each parameter with corresponding number of EOFs/CCAs and predictors used in the CCA model is presented. The cases with two skilful predictors are also presented. The non-skilful cases are shaded in yellow.

Station	p_{01}		p_{11}		μ		K	
	No EOFs, CCAs, predictor	*Skill*	*No EOFs Predictor, CCAs, predictor*	*Skill*	*No EOFs, CCAs, predictor*	*Skill*	*No EOFs, CCAs, predictor*	*Skill*
1. Drobeta Tr.Severin	3+3,2 SLP+SH	60/82	4+6,3 Q 5+5,5 SLP+SH	14/51 28/55	3+3,3 Q	30/57	3+4, 2 SH	15/39
2. Tg. Jiu	3+3,2 SLP+SH	60/82	4+6,3 Q 4+4,3 SLP+Q	25/58 50/71	3+3,3 Q	21/46	3+5,2 SH	26/51
3. Craiova	3+3,2 SLP+SH	55/76	4+6,3 Q 4+4,3 SLP+Q	42/65 47/70	3+7,2 Q	31/57	3+8, 2 SH	14/39
4. Pitesti	3+3,2 SLP+SH	44/67	4+6,3 Q	42/65	4+4,4 Q	2/20	2+6, 1 SH	2/14
5. Tirgoviste	3+3,2 SLP+SH 3+5,2 Q	46/69 64/82	4+4,1 Q	22/52	3+6, 1 Q	7/26	2+6, 2 SH	5/22
6. Ploiesti	3+3,2 SLP+SH 3+5,2 Q	45/68 48/73	4+4,3 Q	39/63	2+2,2 Q	6/46	2+6, 1 SH	-5/-1
7. Calarasi	3+3,2 SLP+SH	18/43	4+4,3 Q	40/64	3+3,3 Q	25/50	3+7, 2 SH	8/31
8. Buzau	3+3,2 SLP+SH	39/64	4+6,3 Q	38/62	3+3,3 Q	27/53		

9. Constanta	3+3, 2 SLP+SH	29/61	4+6,2 Q 4+6,3 Q	41/65 38/61	3+6, 1 Q	-11/-8	3+7,3 SH	17/45
10. Braila	3+3,2 SLP+SH	14/37	4+4,1 Q	14/39	3+6, 1 Q	-9/-5	2+6, 1 SH	-4/-7

Table 2. Same as in Table 1 but for summer.

Station	p_{01}		p_{11}		μ		k	
	No EOFs, CCAs, predictor	*Skill*	*No EOFs, CCAs, predictor*	*Skill*	*No EOFs, CCAs, predictor*	*Skill*	*No EOFs, CCAs, predictor*	*Skill*
1. Drobeta Tr.Severin	7+7,7 Q	47/68	2+4,1 Q	5/40	2+7,2 SH	-4/10	3+3,3 Q	2/19
2. Tg. Jiu	4+4,3 Q	22/48	2+4,1 Q 2+5,2 SH	1/9 7/26	2+7,2 SH	9/30	4+4,4 Q 2+7,2 SH	0/18 9/30
3. Craiova	3+3,2 Q	25/54	3+7,2 Q	30/55	2+7,2 SH	9/30	4+4,2 Q	18/43
4. Pitesti	3+4,2 Q	0.0/25	4+7,2 Q	27/52	3+7,2 SH 3+7,2 Q	2/16 20/44	5+7,1 Q 3+6,2 SH	0/8 6/32
5. Tirgoviste	3+4,2 Q	22/47	3+8,1 Q	3/18	5+5,5 Q	20/48	3+5,3 Q	2/16
6. Ploiesti	3+4,2 Q	19/43	4+7,2 Q	18/43	3+7,2 SH	1/15	5+7,1 Q	6/33
7. Calarasi	3+4,2 Q	28/54	2+6,1 Q	7/29	5+5,2 SH	40/67	4+4,4 Q	18/44
8. Buzau	5+5,5 Q	27/52	4+7,2 Q	6/28	3+3,3 SH 5+5,2 Q	4/19 6/25	-	-
9. Constanta	5+5,5 Q	17/45	2+6,1 Q	2/23	2+7,2 SH	9/33	4+4,4 Q	0/18
10. Braila	5+5,5 Q	24/50	3+8,1 Q $+6,2 SH	0/-18 10/32	5+5,5 Q	23/48	4+4,4 Q	0/13

Table 3. Statistics of winter precipitation regime (maximum duration of dry and wet intervals $\mathbf{d}_{\mathbf{dry}}^{\max}, \mathbf{d}_{\mathbf{wet}}^{\max}$, mean duration of dry and wet intervals $\mathbf{d}_{\mathbf{dry}}^{\mathbf{mean}}, \mathbf{d}_{\mathbf{wet}}^{\mathbf{mean}}$, daily mean /standard deviation of precipitation within rainy days $\mathbf{pp}_{\mathrm{mean}}$, $\mathbf{pp}_{\mathrm{sd}}$, expected maximum of daily precipitation amount $\mathbf{pp}^{\max}$) at 10 Romanian stations derived directly from observations (1951-1974) and indirectly through the stochastic conditional model with parameters calibrated over the period 1974-1999. The 90% confidence intervals are also presented in parentheses.

Station		pp_{mean}	pp_{sd}	pp^{max}	d^{max}_{dry}	d^{max}_{wet}	d^{mean}_{dry}	d^{mean}_{wet}
1. Braila	Obs.	4.5	6.8	51.9	27.0	8.0	4.3	2.0
	Estim.	2.9	3.4	25.2	31.3	8.4	5.2	1.8
		[2.7, 3.1]	[3.1, 3.8]	[18.0, 34.9]	[23, 44]	[6, 11]	[4.8, 5.7]	[1.7, 1.9]
2. Buzau	Obs.	3.5	5.4	37.4	25	8	4.1	2.1
	Estim.	2.9	3.5	26.2	28.9	8.9	4.7	1.8
		[2.7, 3.1]	[3.1, 3.9]	[19.1, 36.3]	[21, 40]	[6,12]	[4.4, 5.1]	[1.7, 1.9]
3. Calarasi	Obs.	3.3	4.9	44.4	27	10	3.5	2.3
	Estim.	2.9	3.5	26.2	24.6	9.7	4.1	1.9
		[2.7, 3.2]	[3.1, 3.9]	[19.4, 36.4]	[18, 34]	[7, 13]	[3.8, 4.4]	[1.8, 2.0]
4. Craiova	Obs.	3.8	5.1	38.1	25	9	3.6	2.4
	Estim.	4.6	5.8	45.9	28.7	12.5	4.3	2.3
		[4.3, 5.0]	[5.2, 6.4]	[33.3, 64.4]	[20, 41]	[9, 17]	[4.0, 4.6]	[2.2, 2.5]
5. Constanta	Obs.	3.6	5.0	46.7	27.0	11.0	3.5	2.1
	Estim.	2.9	3.7	27.8	26.8	9.2	4.6	1.8
		[2.6, 3.1]	[3.2, 4.1]	[20.3, 38.8]	[20, 37]	[7, 13]	[4.2, 4.9]	[1.7, 2.0]
6. Dr.Tr.Severin	Obs.	5.1	7.0	55.6	26.0	12.0	3.5	2.6
	Estim.	4.6	5.7	44.7	28.5	16.4	4.5	2.5
		[4.3, 5.0]	[5.2, 6.3]	[33.3, 60.8]	[21, 41]	[11, 24]	[4.1, 4.8]	[2.3, 2.7]
7. Pitesti	Obs.	4.1	5.5	38.5	25.0	11.0	3.8	2.4
	Estim.	3.9	4.8	36.8	28.9	12.7	4.6	2.2
		[3.6, 4.3]	[4.3, 5.4]	[27.1, 50.2]	[21, 41]	[9, 18]	[4.2, 4.9]	[2.1, 2.4]
8, Ploiesti	Obs.	4.1	5.9	36.8	25.0	12.0	4.0	2.4
	Estim.	3.7	4.7	35.8	28.1	10.3	4.4	2.0
		[3.4, 4.0]	[4.2, 5.2]	[26.8, 50.2]	[20, 40]	[8, 14]	[4.1, 4.7]	[1.9, 2.1]
9. Tg. Jiu	Obs.	5.5	7.5	71.4	25.0	12.0	3.6	2.5
	Estim.	5.0	6.1	46.9	30.1	17.0	4.8	2.5
		[4.6, 5.4]	[5.5, 6.7]	[34.9, 63.8]	[22, 42]	[12, 26]	[4.4, 5.2]	[2.3, 2.7]
10. Targoviste	Obs.	3.9	5.4	37.4	25.0	11.0	3.9	2.4
	Estim.	3.7	4.3	32.0	29.2	10.9	4.7	2.1
		[3.4, 4.0]	[3.9, 4.7]	[23.9, 43.8]	[21, 41]	[8, 15]	[4.4, 5.1]	[2.0, 2.2]

Table 4. Same as in Table 3 but for summer.

Station		pp^{mean}	pp^{SD}	pp^{max}	d^{max}_{dry}	d^{max}_{wet}	d^{mean}_{dry}	d^{mean}_{wet}
1. Braila	Obs.	7.0	11.0	108.0	31.0	10.0	5.1	1.7
	Estim.	6.2	7.6	57.0	27.2	7.5	4.5	1.7
	Confid.	[5.7, 6.8]	[6.7, 8.5]	[41.4, 79.6]	[20, 38]	[6, 10]	[4.2, .9]	[1.6, .8]
2. Buzau	Obs.	7.2	10.5	66.6	28.0	8.0	3.9	1.8
	Estim.	6.7	8.2	62.8	23.3	8.6	3.9	1.8
	Confid.	[6.1, 7.2]	[7.3, 9.1]	[46.1, 86.7]	[17, 33]	[7, 11]	[3.6, 4.1]	[1.7, 1.9]
3. Calarasi	Obs.	6.9	10.1	55.3	29.0	7.0	4.4	1.8
	Estim.	5.6	6.9	53.6	25.9	7.5	4.3	1.6
		[5.2, 6.1]	[6.2, 7.8]	[37.6, 76.3]	[19, 36]	[6, 10]	[4.0, 4.6]	[1.6, 1.7]
4. Craiova	Obs.	5.8	8.9	84.8	19.0	10.0	3.8	1.8
	Estim.	6.1	8.0	63.5	23.2	9.9	3.9	1.8
	.	[5.6, 6.6]	[7.2, 8.9]	[46.1, 87.9]	[17, 32]	[7, 14]	[3.6, 4.2]	[1.8, 2.0]
5. Constanta	Obs.	5.1	8.7	69.9	28.0	6.0	5.5	1.5
	Estim.	5.0	6.0	43.8	30.0	6.8	5.0	1.6
		[4.6, 5.4]	[5.3, 6.7]	[31.4, 60.8]	[22, 41]	[5, 9]	[4.6, 5.4]	[1.5, 1.7]
6. Dr. Tr. Severin	Obs.	6.9	12.2	171.7	31.0	6.0	4.2	1.7
	Estim.	5.6	7.1	55.4	26.0	7.8	4.3	1.7
	.	[5.1, 6.0]	[6.4, 8.0]	[39.4, 78.4]	[19, 36]	[6, 10]	[4.0, 4.6]	[1.6, 1.8]
7. Pitesti	Obs.	7.2	10.5	84.7	20.0	11.0	3.6	2.0
	Estim.	6.9	8.8	69.5	19.2	10.1	3.3	1.9
		[6.4, 7.4]	[8.0, 9.7]	[51.6, 96.7]	[14, 26]	[7, 15]	[3.1, .5]	[1.8, 2.0]
8, Ploiesti	Obs.	6.7	9.7	62.2	28.0	10.0	3.2	1.9
	Estim.	6.5	8.4	67.0	18.1	10.3	3.1	2.0
	.	[6.1, 7.0]	[7.6, 9.2]	[50.1, 91.7]	[13, 25]	[8, 14]	[3.0, 3.3]	[1.9, 2.1]
9. Tg. Jiu	Obs.	7.7	11.2	79.3	17.0	8.0	3.4	1.9
	Estim.	7.0	9.2	73.9	21.6	9.4	3.6	1.9
		[6.5, 7.5]	[8.3, 10.1]	[54.6, 100.9]	[16, 30]	[7, 13]	[3.3, 3.8]	[1.8, 2.0]
10. Targoviste	Obs.	8.1	11.1	85.0	20.0	8.0	3.5	1.8
	Estim.	7.4	9.3	74.0	17.8	9.4	3.1	1.9
		[6.8, 7.9]	[8.4, 10.2]	[54.6, 102.2]	[13, 24]	[7, 13]	[2.9, 3.3]	[1.8, 2.0]

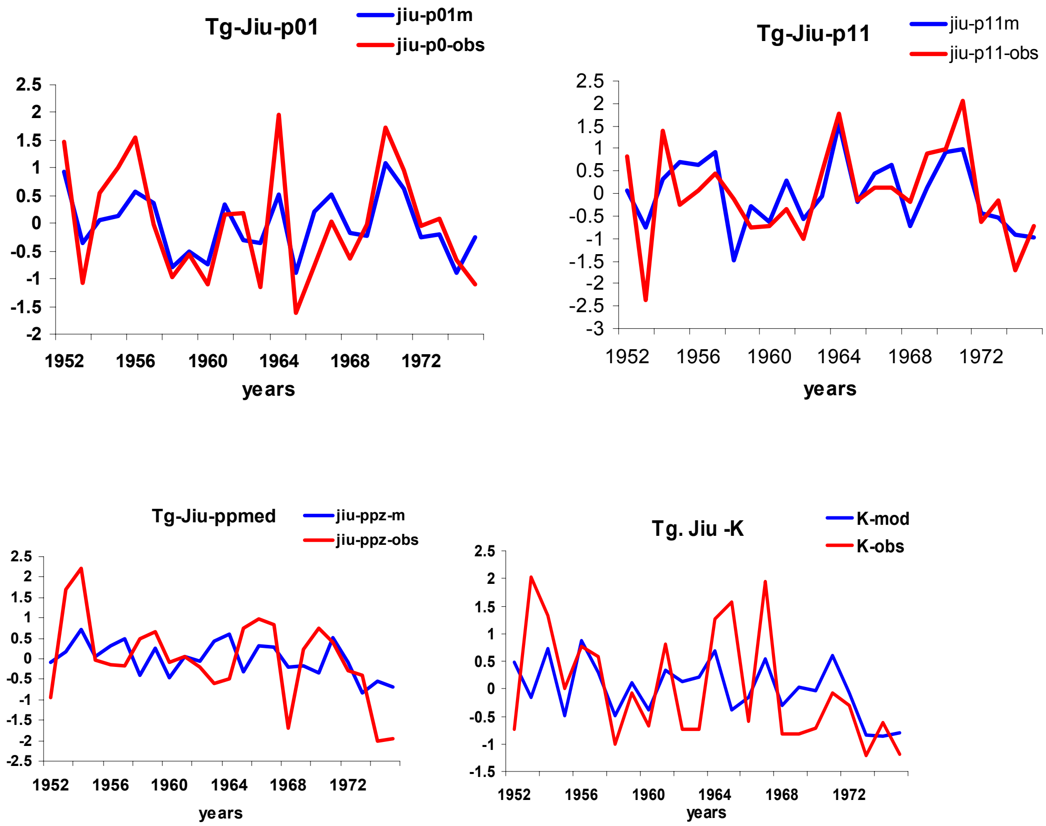
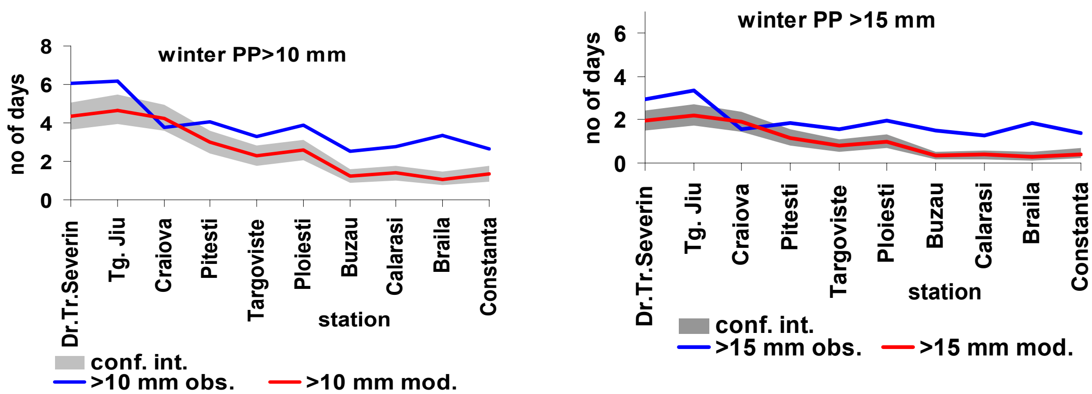


Figure 2. Winter standardized anomalies of the precipitation distribution parameters for the period 1952-1974, derived from observations (red line) and derived indirectly through the CCA model (blue line) fitted to the 1975-1999 data.

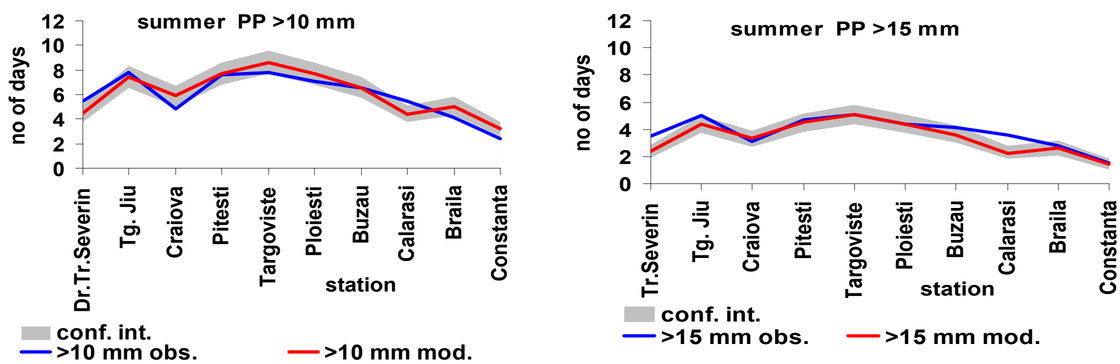
3.2. Accuracy of the conditional stochastic model

Using the most skilful CCA models for each of the four parameters, the daily time series were generated and precipitation statistics were calculated. Firstly, these parameters are used in the Markov chain model to generate daily time series of precipitation. The daily precipitation amount is randomly generated using a gamma distribution. The performance of the conditional stochastic model is assessed in terms of how well it reproduces the statistical features of the precipitation time series presented in Section 2. These features are represented by: maximum duration of dry and wet intervals ($\mathbf{d}_{\mathbf{dry}}^{\max}, \mathbf{d}_{\mathbf{wet}}^{\max}$), mean duration of dry and wet intervals ($\mathbf{d}_{\mathbf{dry}}^{\mathbf{mean}}, \mathbf{d}_{\mathbf{wet}}^{\mathbf{mean}}$), daily mean /standard deviation of precipitation within rainy days (pp_{mean}, pp_{sd}), expected maximum of daily precipitation amount (pp_{max}) and frequency distributions of daily precipitation within/exceeding various intervals. After running the conditional model 1000 times, a distribution of these parameters is achieved. Then, the ensemble mean and their 90% confidence intervals of the respective parameters were computed and these values are considered as expectations for these parameters.

Table 3 and 4 summarize the results over the independent interval 1951-1974, with the four parameters estimated through the CCA model fitted over the interval 1974-1999, for the winter and summer seasons, respectively. From comparison with the similar parameters calculated from observations it was found that, generally, the model is skilful for cases where the CCA model is skilful in simulating the four precipitation distribution parameters. The maximum duration of wet/dry intervals are generally well reproduced by the conditional stochastic model for both seasons (the observed values are covered by the 90% confidence intervals), while the expected maximum of daily precipitation amount (pp_{max}) is a little underestimated for some stations. The frequency of heavy precipitation (exceeding 10mm, 15mm and 20mm) is well reproduced for summer but it is underestimated for the winter (see Figure 3). The small precipitation amounts ($\leq$ 5 mm) are overestimated for both seasons while the amounts between 5mm and 15mm are well reproduced for winter and overestimated for summer. Other parameters are generally underestimated for both seasons: mean duration of dry and wet intervals, daily mean /standard deviation of precipitation within rainy days. Figure 4 shows the temporal evolution of the winter precipitation amount at the Tg. Jiu station derived from daily time series generated using various predictors and compared to those derived directly from observations. It can be seen that, when one parameter is estimated through a more skilful CCA model, the results are better: p11 is better estimated using the SLP+Q predictor (50% explained variance, 0.70 correlation coefficient), compared with the Q predictor (25% explained variance, 0.58 correlation coefficient) that is the best predictor for almost all stations regarding this parameter. The temporal evolution as well as magnitude of the observed values is well reproduced which is a good surprise for a stochastic model.



Winter



Summer

Figure 3. Seasonal mean of the precipitation frequency exceeding 10/15 mm/day over the period 1951-1974 derived from observations and from generated time series through the conditional stochastic model (as ensemble averages over 1000 runs) with parameters calibrated over the period 1975-1999. 90% confidence intervals are shaded in grey.

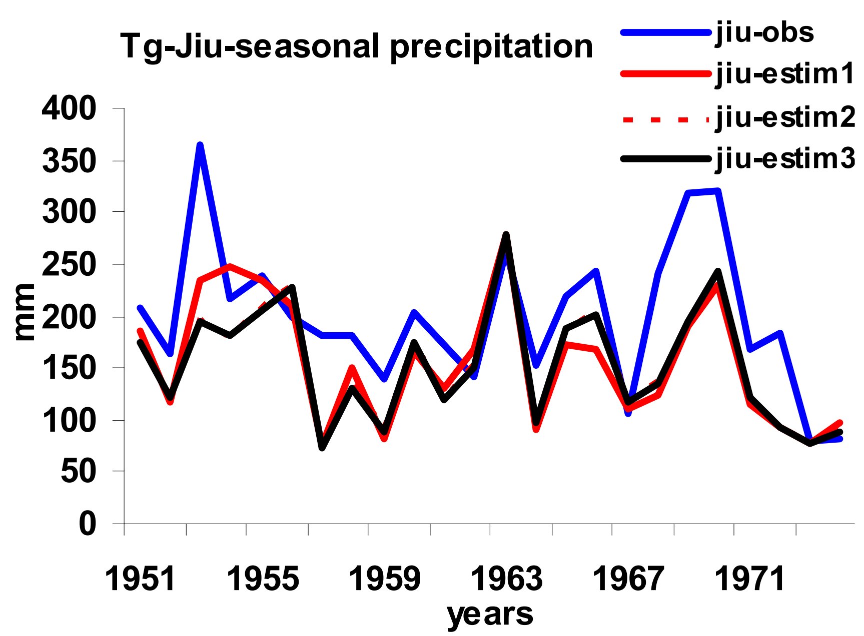


Figure 4. Winter (December-February) precipitation amount at the Tg. Jiu station over the interval 1951-1974 derived from observations (blue line) and indirectly from daily time series generated through the conditional stochastic model fitted over the interval 1974-1999 with parameters estimated by the most skilful CCA model for each parameter: a) SLP+SH (p01), Q (p11, μ), SH(K)-red line; b) same as in a) but using SLP+Q predictor for p11 (the highest skill)-black line; c) same as in b) but with SLP predictor for p11 (similar skill with SLP+SH)-red dashed line, which overlaps the black line.

4. Conclusions

The accuracy of the conditional stochastic model is generally dependent on the accuracy of the CCA model in estimating the four precipitation distribution parameters. The results presented here show that the performance of the CCA model was significantly improved in the case of the summer season, especially for transition probabilities, when the instability and moisture indices were considered as predictors compared with previous studies when only sea level pressure was considered as predictor. For winter, the case of the transition probability from a dry day to a wet day, the SLP predictor gives similar results with those obtained by using instability/moisture indices alone or by combination with SLP. For the other parameters, the instability/moisture predictors give better results. However, the performance of the CCA model for summer is lower than for winter.

The conditional stochastic model is accurate in reproducing the maximum duration of wet/dry intervals for both seasons, while the expected maximum of daily precipitation amount (pp_{max}) is a little underestimated for some stations. The frequency of heavy precipitation (exceeding 10mm, 15mm and 20mm) is well reproduced for summer but it is underestimated for winter. The small precipitation amounts (≤ 5 mm) are overestimated for both seasons while the amounts between 5mm and 15mm are well reproduced for winter and overestimated for summer.

References

Amos. D.E., 1983: A portable Fortran subroutine for derivates of the PSI function, ACM trans. Math software, Algorithm 610.

Buishand, T.A., M.V. Shabalova, T. Brandsma, 2004; On the Choice of the Temporal Aggregation Level for Statistical Downscaling of Precipitation. *Journal of Climate* **17**, 1816-1827.

Busuioc, A., H. von Storch and R. Schnur, 1999: Verification of GCM generated regional seasonal precipitation for current climate and of statistical downscaling estimates under changing climate conditions, *Journal of Climate* **12**, 258-272.

Busuioc, A., D. Chen and C. Hellström, 2001: Performance of statistical downscaling models in GCM validation and regional climate change estimates: Application for Swedish precipitation. *International Journal of Climatology* **21**, 348-367.

Busuioc, A and H. von Storch, 2003: Conditional stochastic model for generating daily precipitation time series, *Climate Research* **24**, 181-195.

Busuioc, A, Giorgi, F, X. Bi and M. Ionita, 2006: Comparison of regional climate model and statistical downscaling simulations of different winter precipitation change scenarios over Romania. *Theoretical and Applied Climatology* **86**, 101-123, DOI 10.1007/S00704-005-0210-8.

Busuioc, A., Tomozeiu, R. and Cacciamani, C. 2007: Statistical downscaling model for winter extreme precipitation events in Emilia-Romagna region. *International Journal of Climatology*, in press.

Cacciamani C, Battaglia F, Patruno P, Pomi L, Selvini A, Tibaldi S., 1995: A climatological study of thunderstorm activity in the Po Valley. *Theorethical and Applied Climatology* **50**, 185-203.

Coe, R and Stern, RD, 1982: Fitting models to daily rainfall data, *Journal of Applied Meteorology* **21**, 1024-1031.

Huth, R., Kysely, J., and Dubrovsky, M., 2001: Time structure of observed, GCM-simulated, downscaled, and stochastically generated daily temperature series. *Journal of Climate* **14**, 4047-4061.

Kalnay E and coauthors, 1996: The NCEP/NCAR 40-year reanalysis project. *Bulletin of the American Meteorological Society* **77**, 437-471.

Katz R. W., M. B. Parlange and C. Tebaldi, 2003: Stochastic modeling of the effects of large-scale circulation on daily weather in the southeastern U. S. *Climatic Change* **60**, 189-216.

Palutikof, JP, Goodess CM, Watkins SJ and Holt T, 2002: Generating rainfall and temperature scenarios at multiple sites: examples from the Mediterranean. *Journal of Climate* **15**, 3529-3548.

Wilby R.L., O.J. Tomlinson, C.W. Dawson, 2003: Multi-site simulation of precipitation by conditional resampling. *Climate Research* **23**, 183-194.

Wilks, D., 1992: Adapting stochastic weather generation algorithms for climate change studies. *Climate Change* **22**, 67-84.

von Storch, H., E. Zorita, and U. Cubasch, 1993: Downscaling of global climate change estimates to regional scale: An application to Iberian rainfall in wintertime. *Journal of Climate* **6**, 1161-1171.