

European Geosciences Union General Assembly 2015

Vienna, Austria, 12 - 17 April 2015

Session HS7.7/NP3.8: Hydroclimatic and hydrometeorologic stochasticity

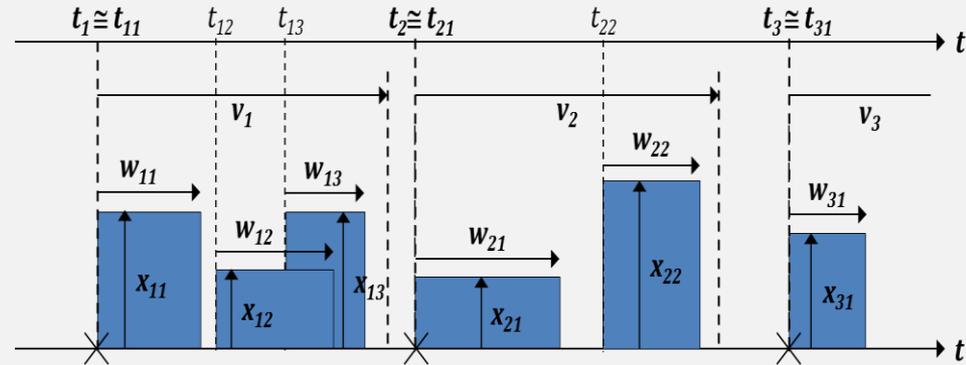
Assessing the performance of Bartlett-Lewis model on the simulation of Athens rainfall

**Panagiotis Kossieris, Andreas Efstratiadis, Ioannis Tsoukalas
and Demetris Koutsoyiannis**

Department of Water Resources & Environmental Engineering
School of Civil Engineering
National Technical University of Athens, Greece

1. Introduction

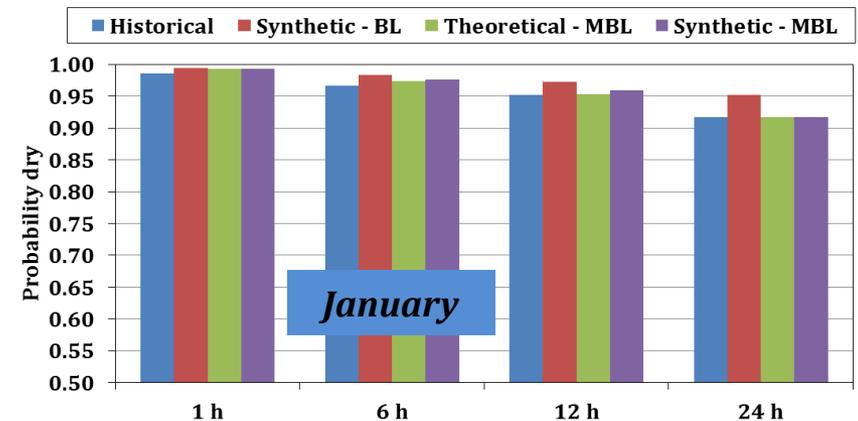
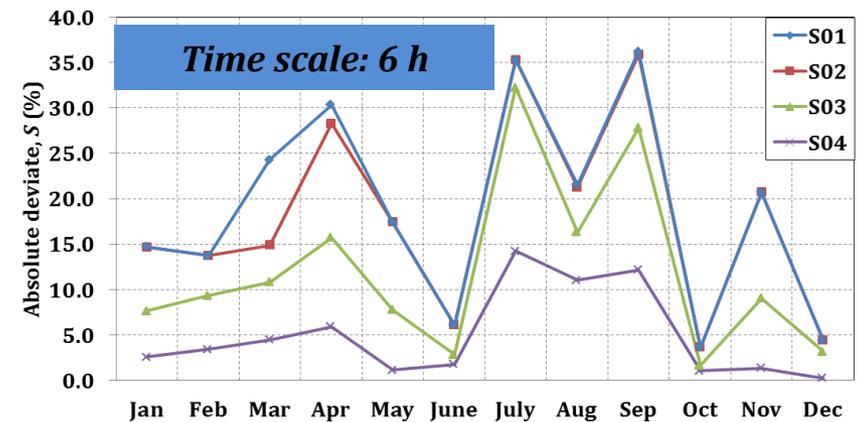
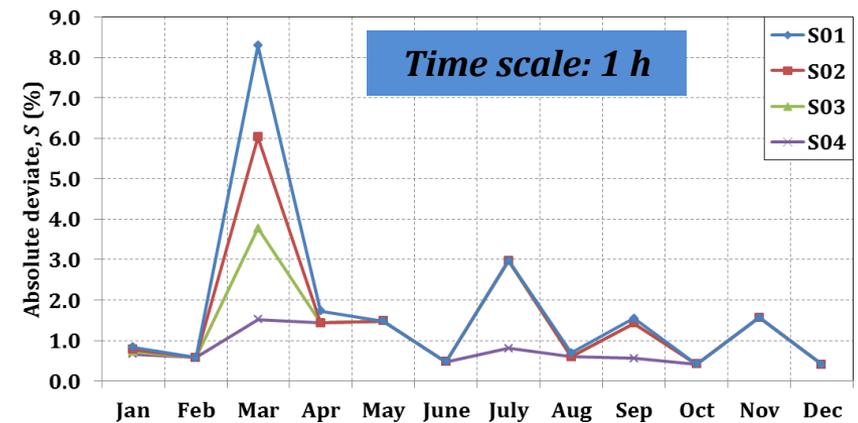
- We examine the performance of two different versions of **Bartlett-Lewis model (BL)** model in **convective** and **frontal rainfall of Athens**.



- Further to **typical statistical characteristics**, explicitly preserved by the model, we also examine important **temporal properties of storms (rainfall events & dry intervals)**, as well as the statistical distribution of **annual rainfall maxima**.
- We focus more on the formulation of the **calibration problem**, by assessing the performance of the BL models against issues such as the choice of the statistics to preserve and the time scales of interest.
- For each month, the **parameters** of the original and modified BL models were **calibrated through the EAS algorithm**, assuming alternative scenarios of the desirable statistical characteristics to preserve.

2. Key findings

- Both models reproduce the statistical characteristics that are implicitly involved in calibration process, showing **poor performance in preserving the rest statistics.**
- Calibration with **different set of statistics lead to different parameter values and model performance**, in terms of preserving the statistical characteristics, especially in the case of the modified BL model.
- Both versions of the BL model fail to reproduce the **significant variability of rainfall events**, due to the overclustering of pulses, which also results to **over-estimation of probability dry**, at the hourly and daily time scales.

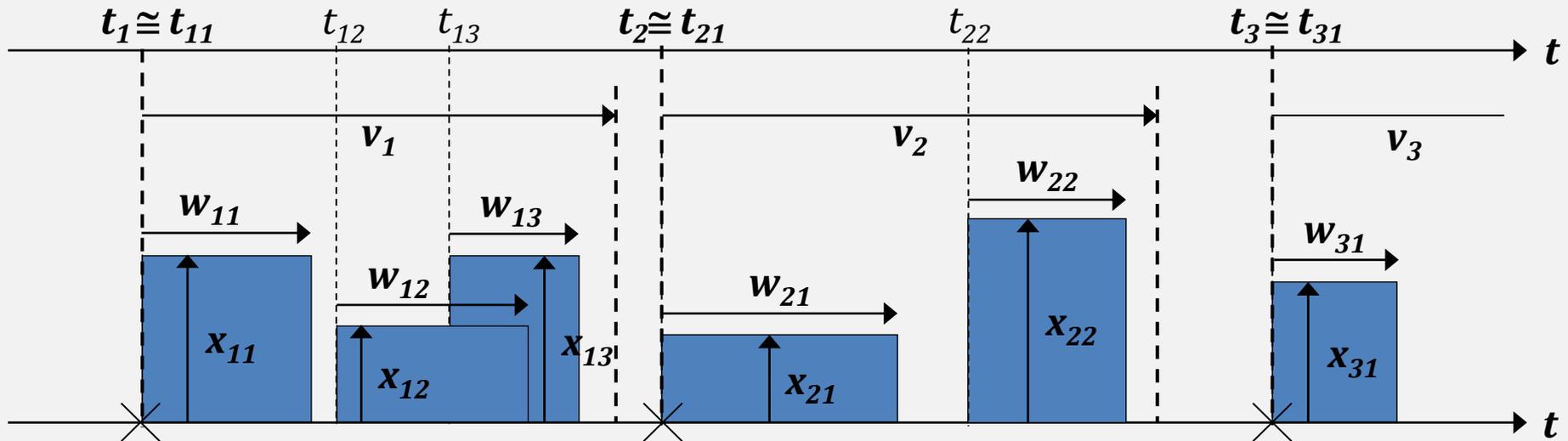


3. The Bartlett-Lewis model

□ Model assumptions (**original version**; Rodriguez-Iturbe *et al.*, 1987):

- **Storm origins** t_i occur in a Poisson process, with rate λ
- **Cell origins** t_{ij} occur in a Poisson process, with rate β
- **Cell arrivals** terminate after time v_i exponentially distributed (parameter γ)
- **Cell durations** w_{ij} are exponentially distributed (parameter η)
- **Cell intensities** x_{ij} are either exponentially or gamma distributed.

□ In the **modified version** (Rodriguez-Iturbe *et al.*, 1988) η is assumed gamma distributed, with scale parameter ν and shape parameter α , and varies for each event, such as β/η and γ/η remain constant.



5. The modified Evolutionary Annealing-Simplex (EAS) method

- ❑ Effective combination of evolutionary search, simulated annealing and downhill simplex (Nelder-Mead) local search method.
- ❑ Evolution is based on **simplex transformations** or **mutation**.
- ❑ Probabilistic transitions, since a stochastic term is added to the objective function, relative to a “temperature” metric, T .
- ❑ **Multiple expansions** and **uphill transitions** are allowed, to accelerate the search and escape from local minima, respectively.
- ❑ The major differences to the original version evolve:
 - ❑ **Dynamic adjustment of shrinkage** coefficient based on T .
 - ❑ **Re-annealing** of the system when T becomes low without further improving the current best point.
- ❑ Recently, a **hybrid combination** of EAS method enhanced with **surrogate-based techniques** is implemented, for time-expensive optimization problems (Tsoukalas *et al.*, 2015).

6. Calibration of BL model

- ❑ The original version of the BL model contains 5 parameters, while the modified 6 or 7 depending on the distribution of cell intensities.
- ❑ For a given set of model parameters, its major statistical properties (mean, variance, covariance function, probability dry) can be analytically computed through theoretical equations.
- ❑ However, the inverse procedure has no analytical solution but can be handled as a calibration problem, by minimizing the distance between the theoretical and the observed statistics.
- ❑ Calibration is governed by several sources of uncertainty:
 - ❑ Different statistical characteristics and distance metrics results to totally different parameter sets, for the same process.
 - ❑ The response surface has numerous local optima, thus making extremely difficult to identify the appropriate parameter set.
 - ❑ A good approximation of the statistical metrics that are accounted for in calibration does not ensure satisfactory representation of other important aspects of the simulated process.

7. Case Study: Simulation of Athens rainfall

- We examined the performance of the original (BL) and modified (MBL) model using hourly rainfall data from the National Observatory of Athens (1927-1996), that were split into 12 monthly sub-sets.
- For each month, the parameters of the original and modified BL models were calibrated through the EAS algorithm, assuming alternative scenarios of the desirable statistical characteristics to preserve.
- Each optimized model configuration was further evaluated using as performance measure the mean absolute deviation, S_i , between the historical and theoretical statistics for time scales $i = 1, 6, 12, 24$ h (kind of **validation for stochastic models**).

Scenarios for original BL model

S01: $Mean^1, Var^1, \rho_1^1, Var^6, \rho_1^6$

S02: $Mean^1, Var^1, \rho_1^1, Var^{24}, \rho_1^{24}$

S03: $Mean^1, Var^1, \rho_1^1, Var^{12}, \rho_1^{12}$

S04: *Statistics from all time scales*

Scenarios for modified BL model

SM1: $Mean^1, Var^1, \rho_1^1, pdr^1, Var^{24}, pdr^{24}$

SM2: $Mean^1, Var^1, \rho_1^1, pdr^1, \rho_1^{24}, pdr^{24}$

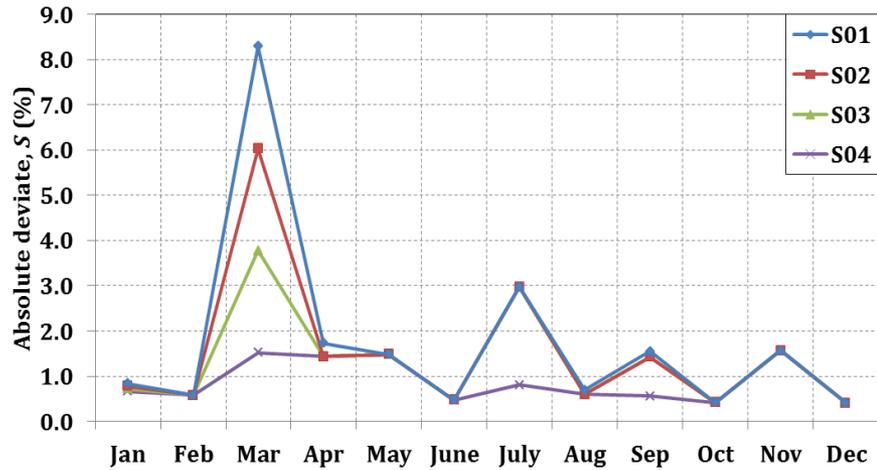
SM3: $Mean^1, Var^1, \rho_1^1, pdr^1, Var^6, pdr^{24}$

SM4: $Mean^1, Var^1, \rho_1^1, pdr^1, \rho_1^6, pdr^{24}$

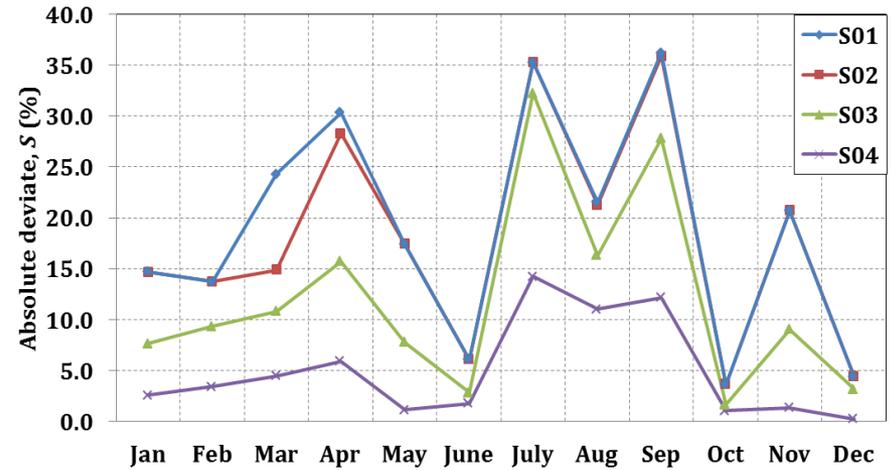
SM5: *Statistics from all time scales*

Notation: $Mean^k$: average rainfall at the k -hour scale (e.g. $Mean^1$ = hourly mean); Var^k : variance; ρ_1^k : lag-1 autocorrelation; pdr^k : probability dry

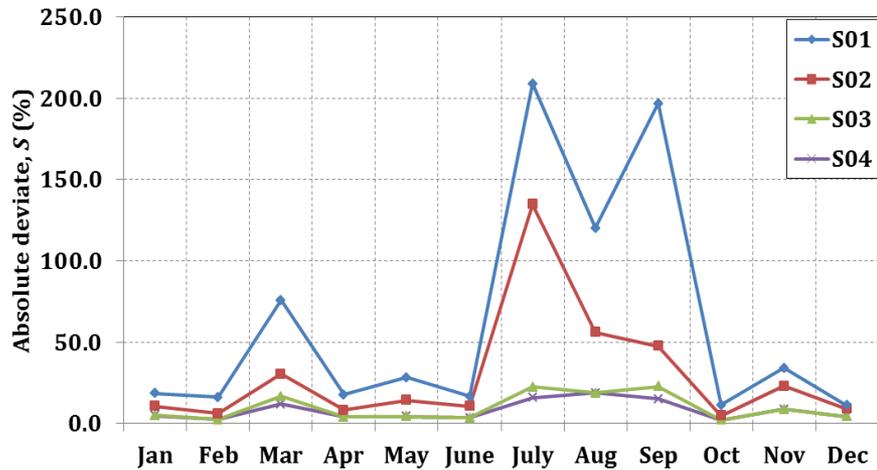
8. Validation of BL model



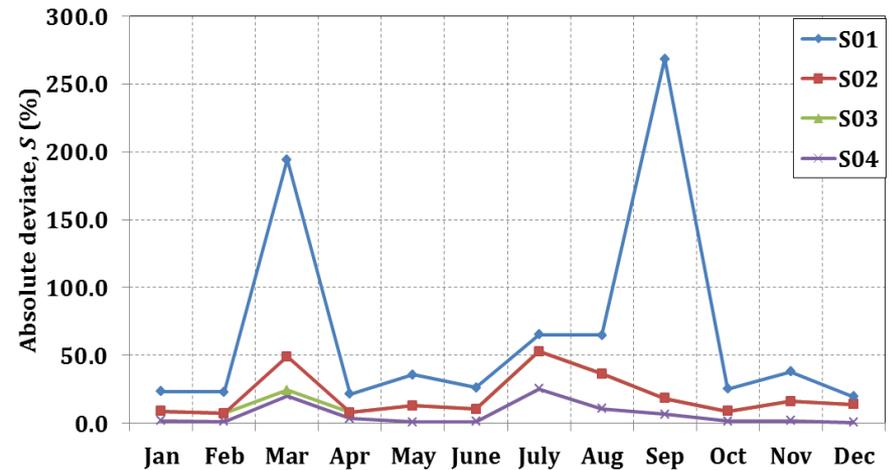
Time scale: 1 hour



Time scale: 6 hours

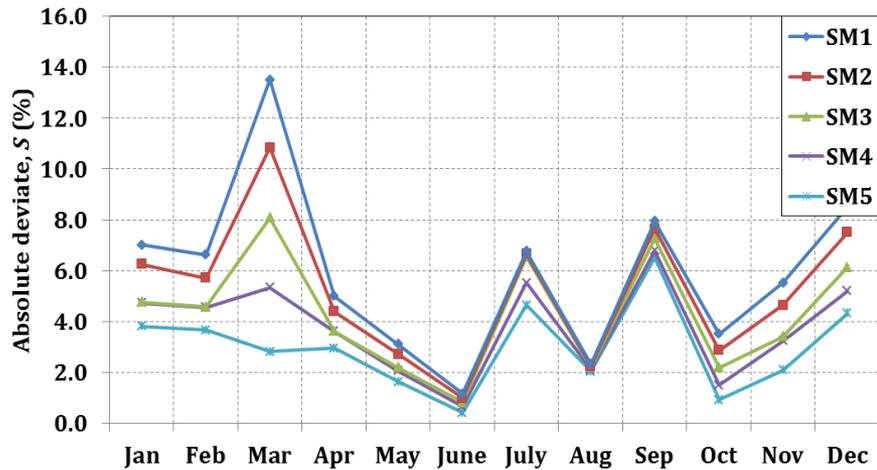


Time scale: 24 hours

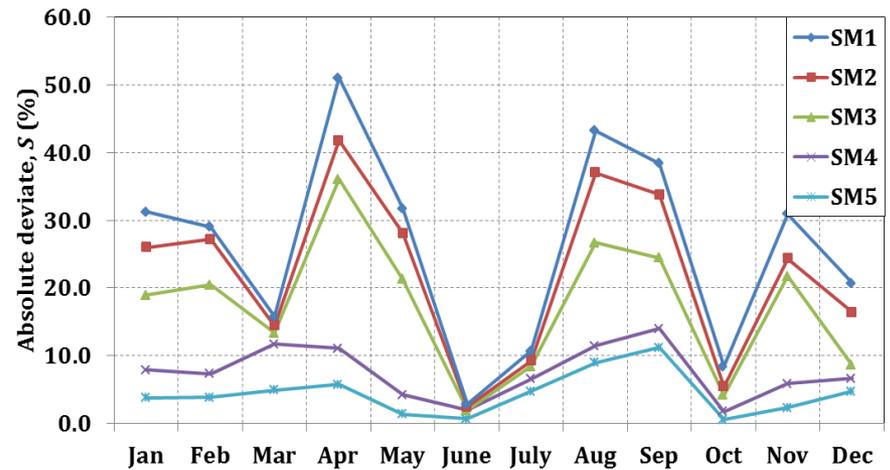


All time scales

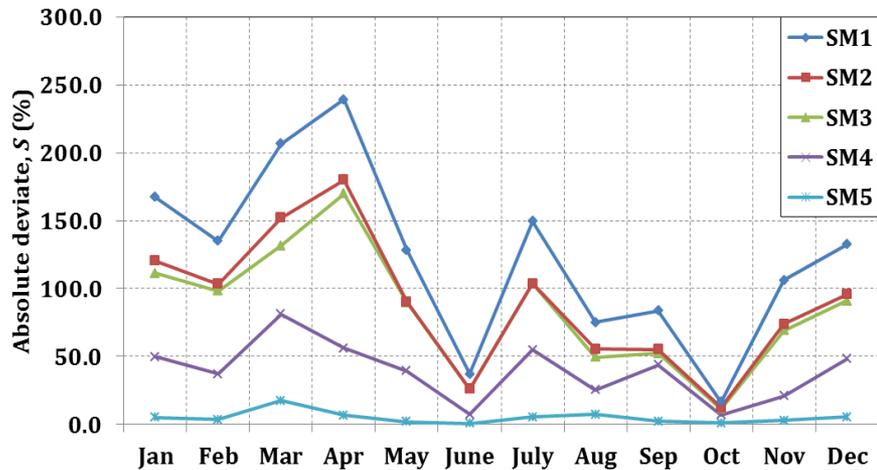
9. Validation of MBL model



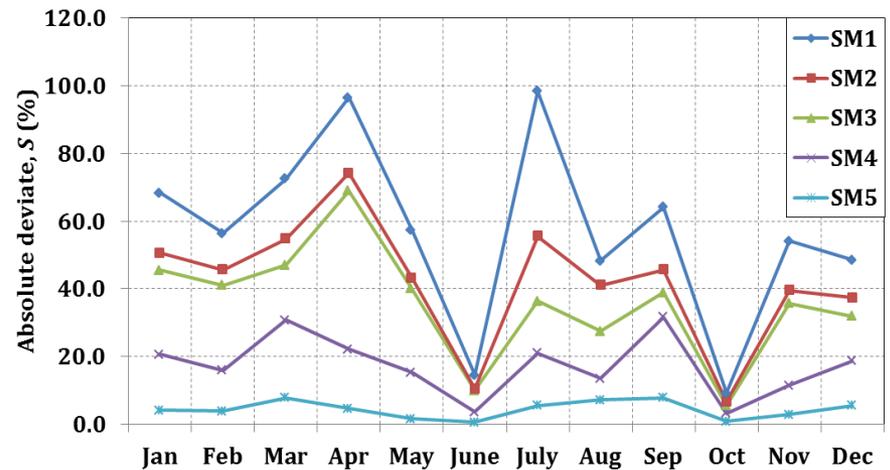
Time scale: 1 hour



Time scale: 6 hours

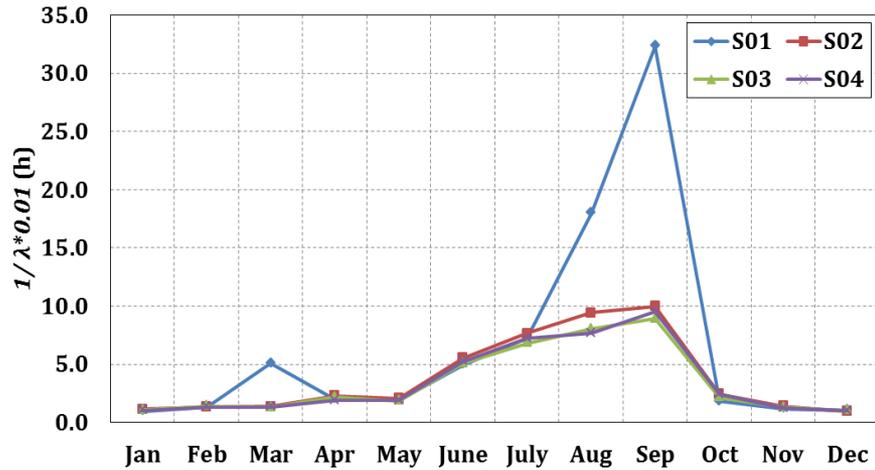


Time scale: 24 hours

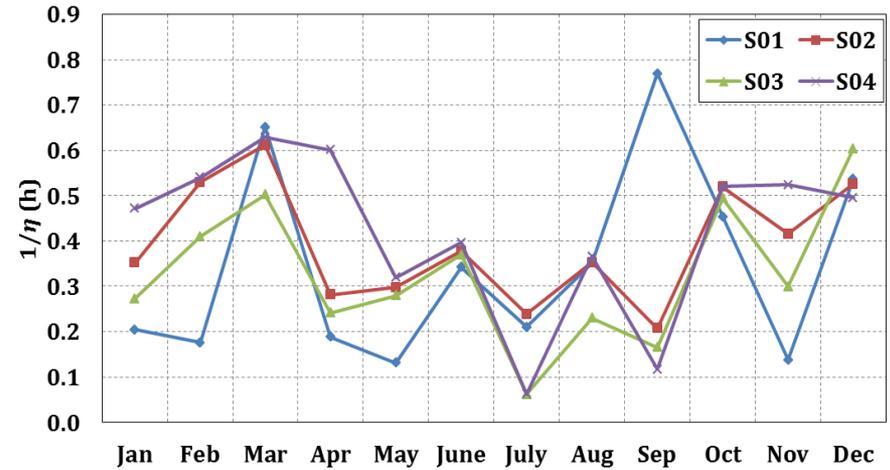


All time scales

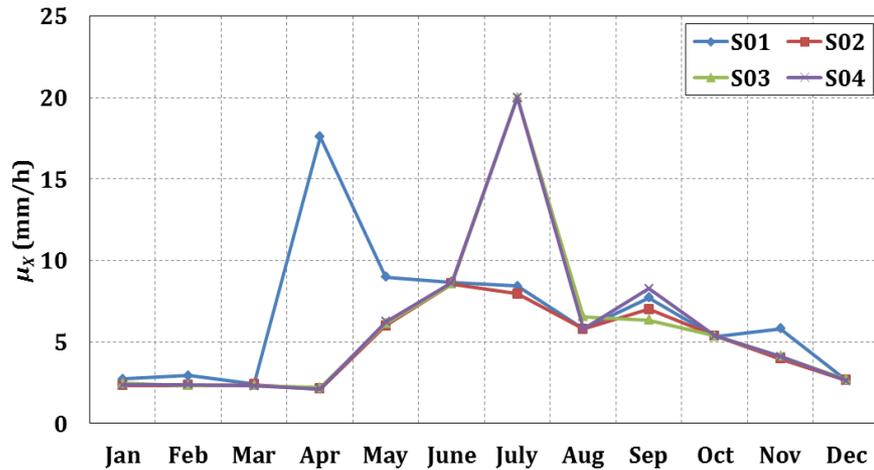
10. Optimized parameters of BL model



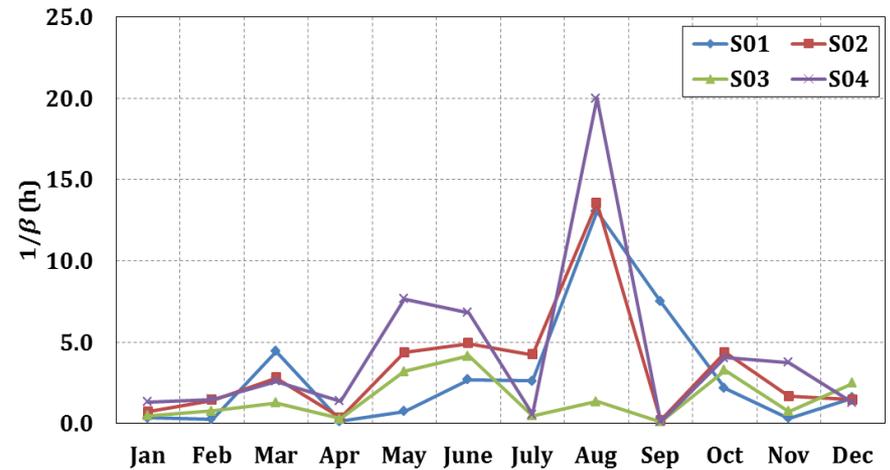
Mean interval between storms



Mean cell duration

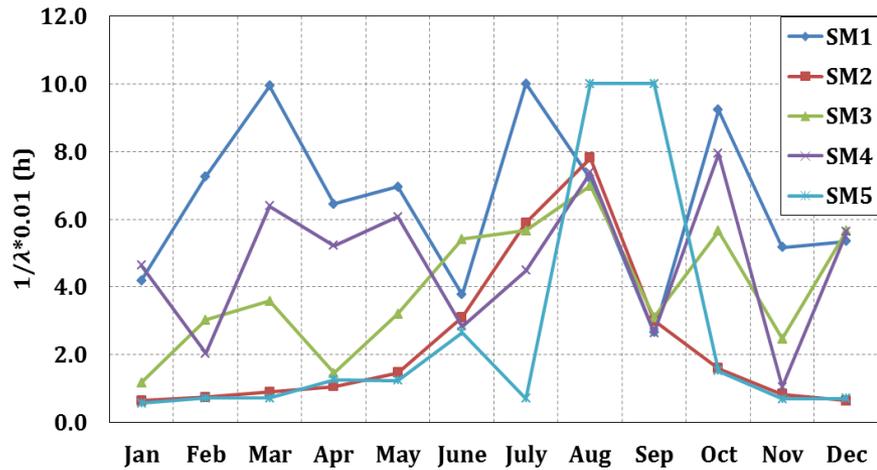


Mean cell intensity

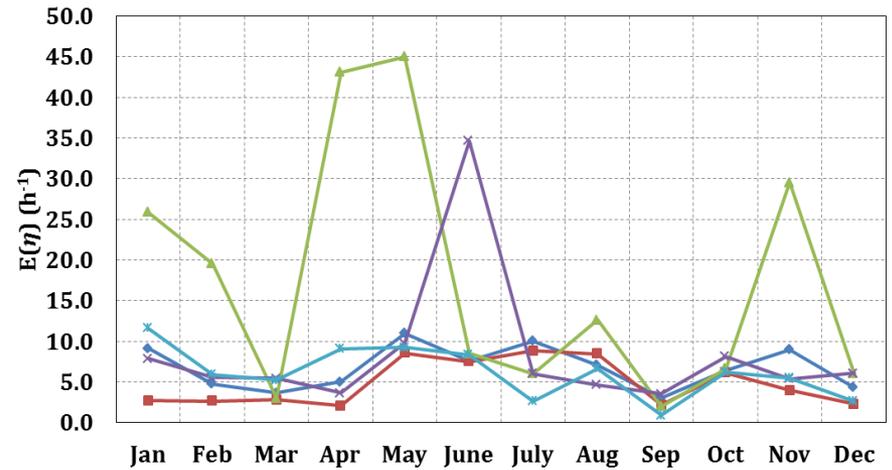


Mean interval between cells

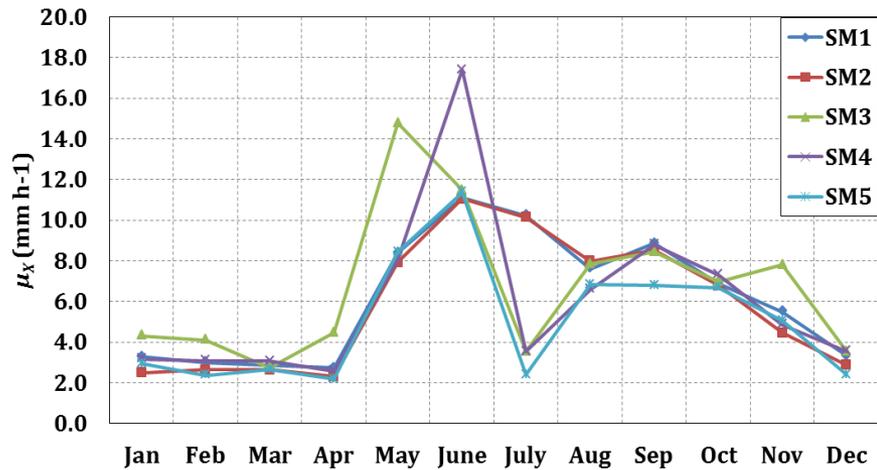
11. Optimized parameters of MBL model



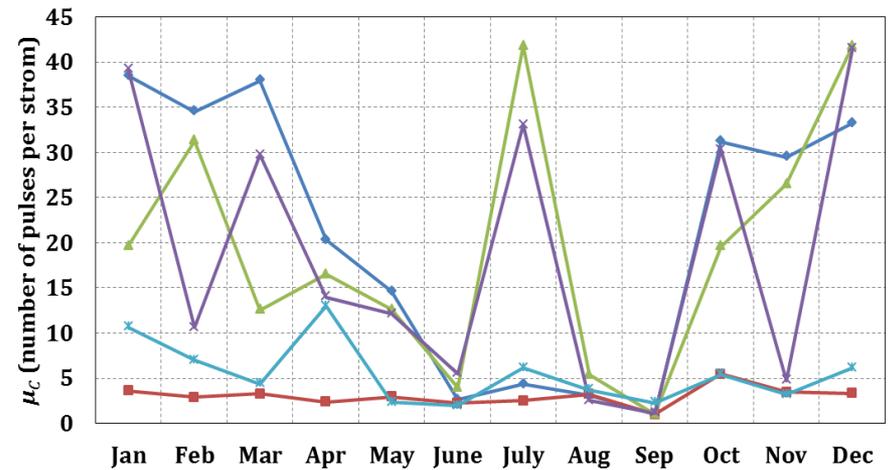
Mean interval between storms



Mean cell duration



Mean cell intensity



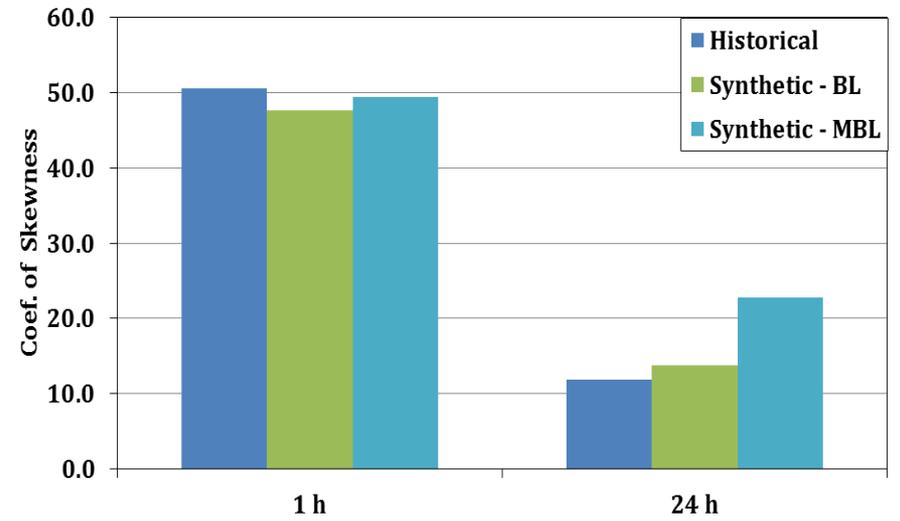
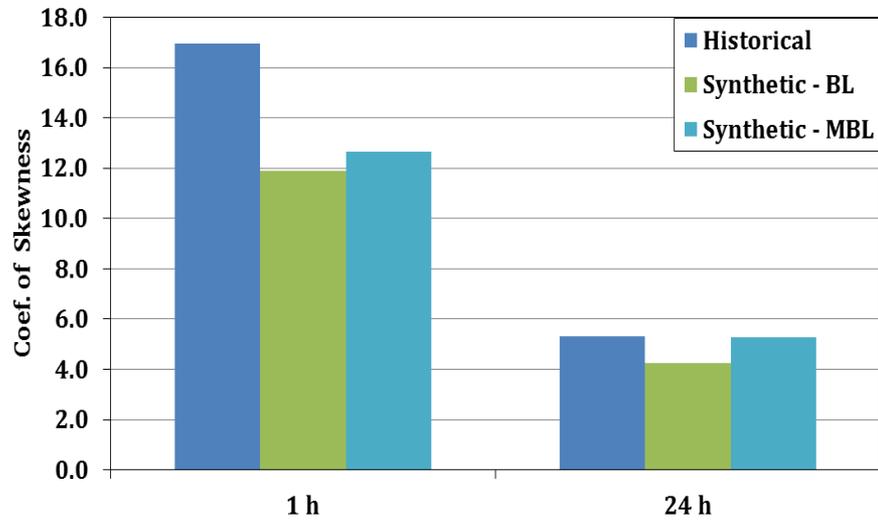
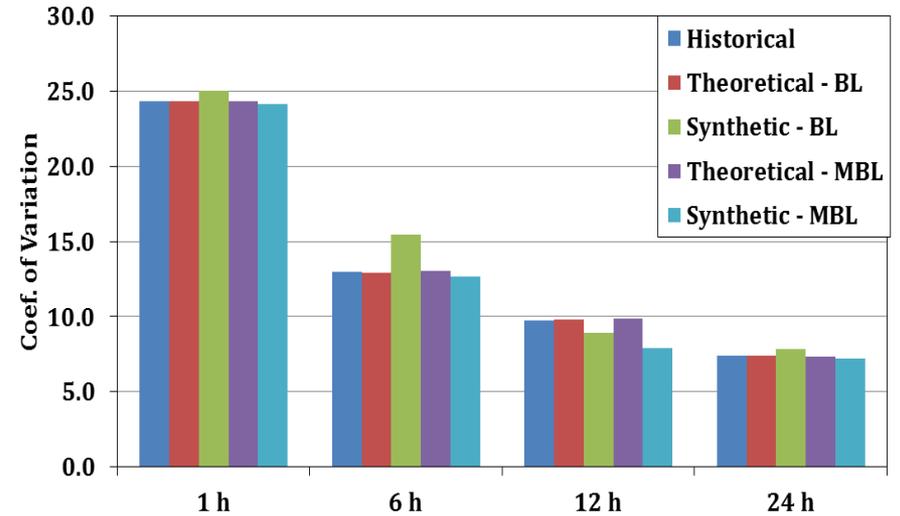
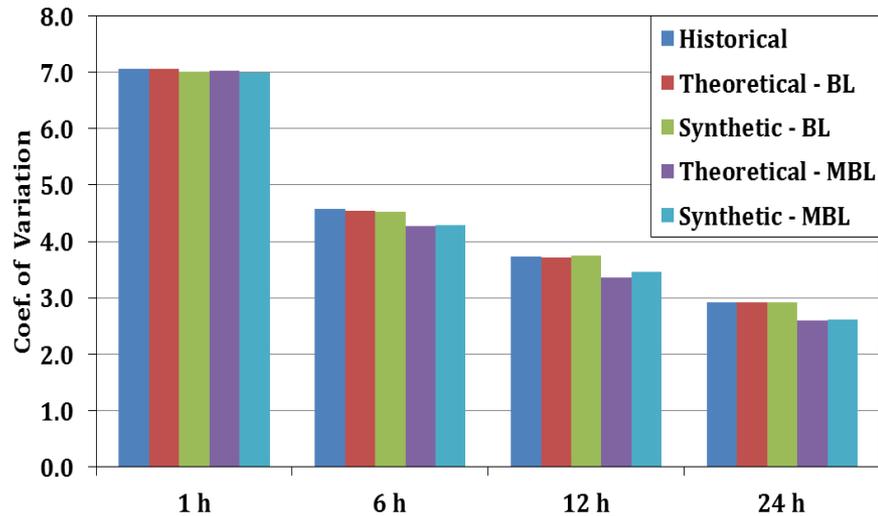
Mean number of cells per storm

12. Evaluation of synthetic rainfall data

- ❑ We compare the performance of BL and MBL models in reproducing the statistical characteristics of synthetic rainfall of 1000 years length.
- ❑ The synthetic data were generated via HyetosR, assuming the optimized parameters of scenarios S02 and SM2, respectively.
- ❑ We emphasize the statistical characteristics of two particular months, with substantially different meteorological regime (January - frontal storms; June – convective storms).

	Historical	Theoretical - BL	Synthetic - BL	Theoretical - MBL	Synthetic - MBL	
Average (mm)	0.065	0.065	0.065	0.065	0.065	January, Hourly Statistics
St. Deviation (mm)	0.458	0.458	0.458	0.458	0.457	
Coef. of Skewness	16.957	-	11.884	-	12.663	
Average (mm)	1.555	1.555	1.557	1.563	1.563	January, Daily Statistics
St. Deviation (mm)	4.532	4.532	4.535	4.053	4.083	
Coef. of Skewness	5.301	-	4.235	-	5.289	
Average (mm)	0.015	0.015	0.015	0.015	0.015	June, Hourly Statistics
St. Deviation (mm)	0.370	0.370	0.375	0.370	0.374	
Coef. of Skewness	50.578	-	47.684	-	49.428	
Average (mm)	0.365	0.365	0.360	0.365	0.365	June, Daily Statistics
St. Deviation (mm)	2.694	2.694	2.822	2.692	2.638	
Coef. of Skewness	11.881	-	13.807	-	22.757	

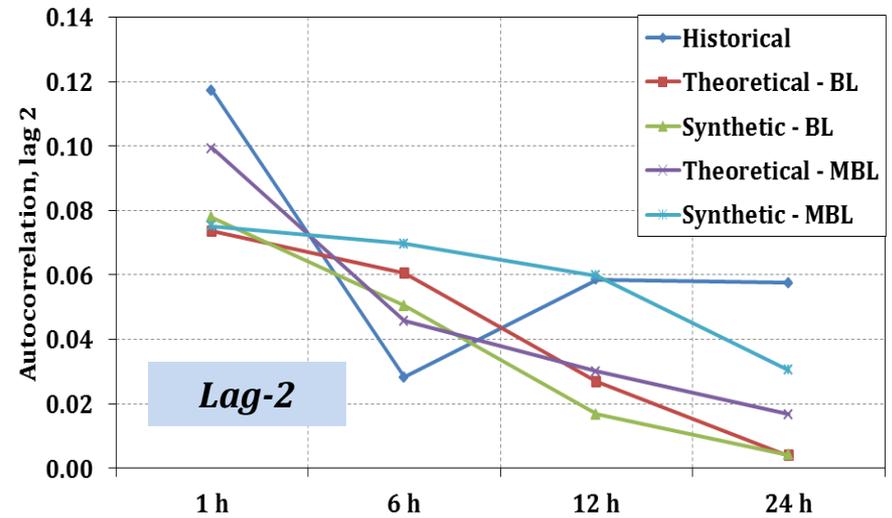
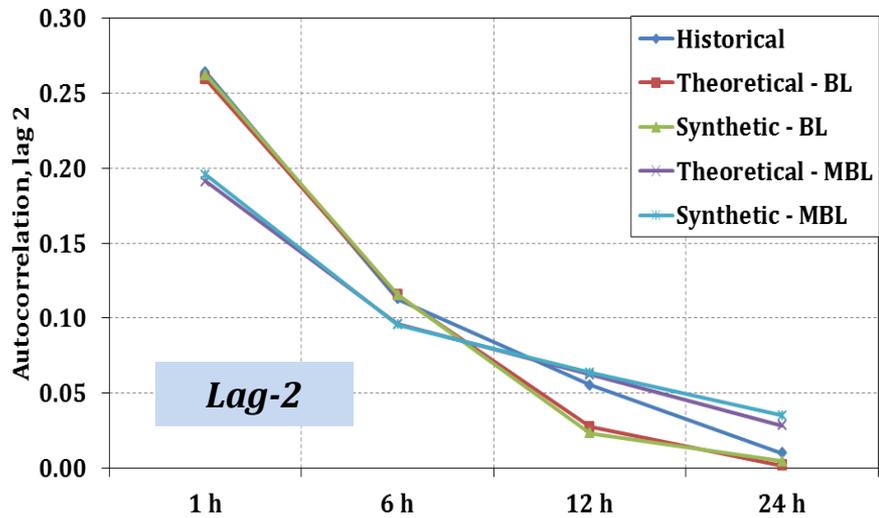
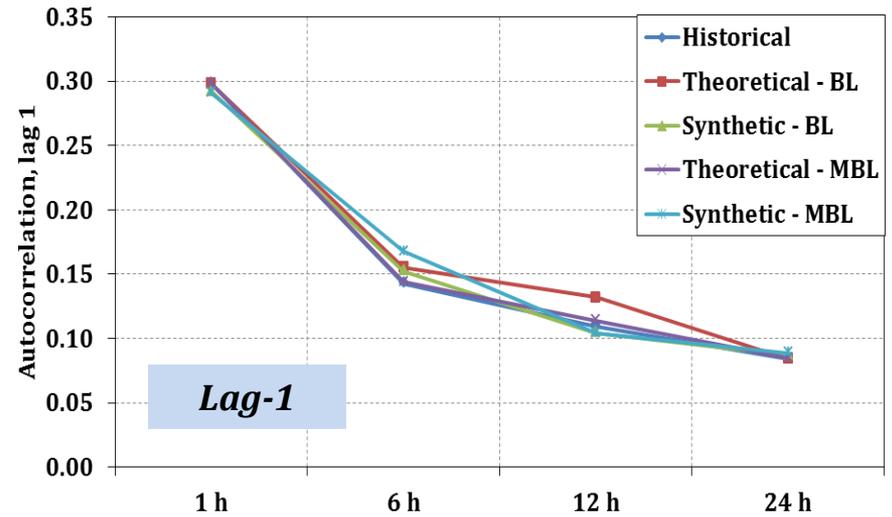
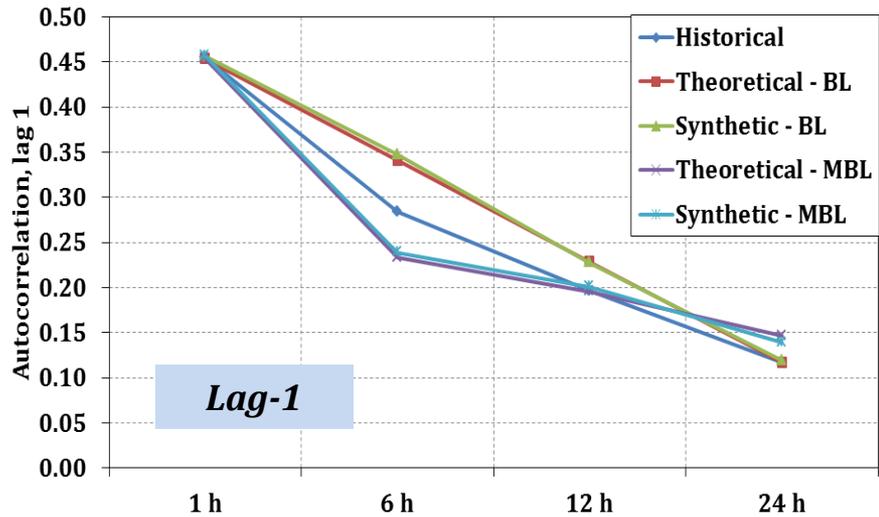
13. Results for variability and skewness



January

June

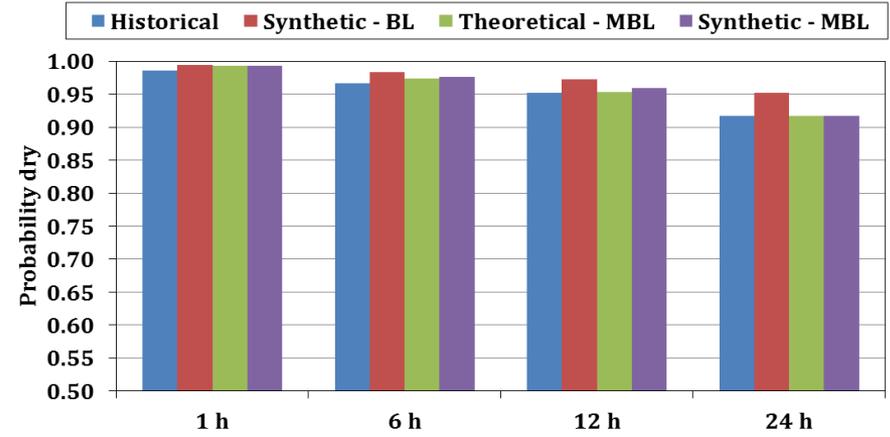
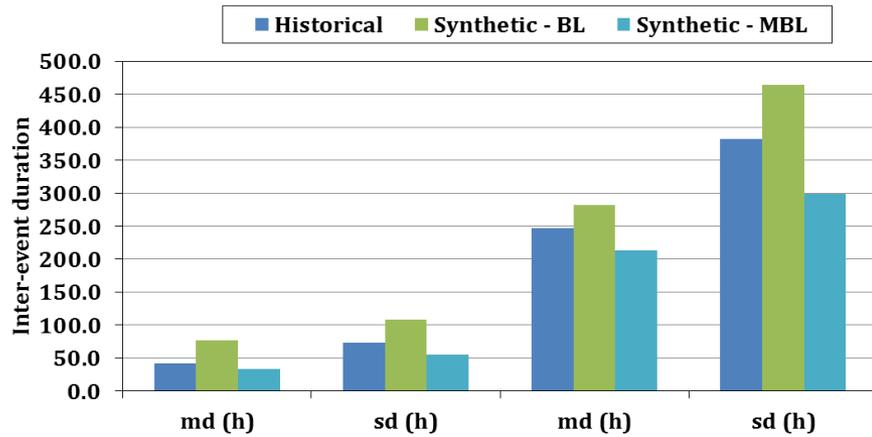
14. Reproduction of autocorrelations



January

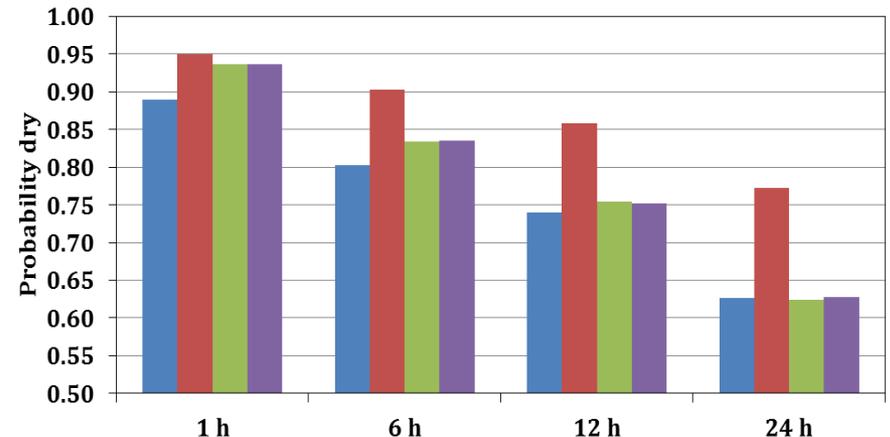
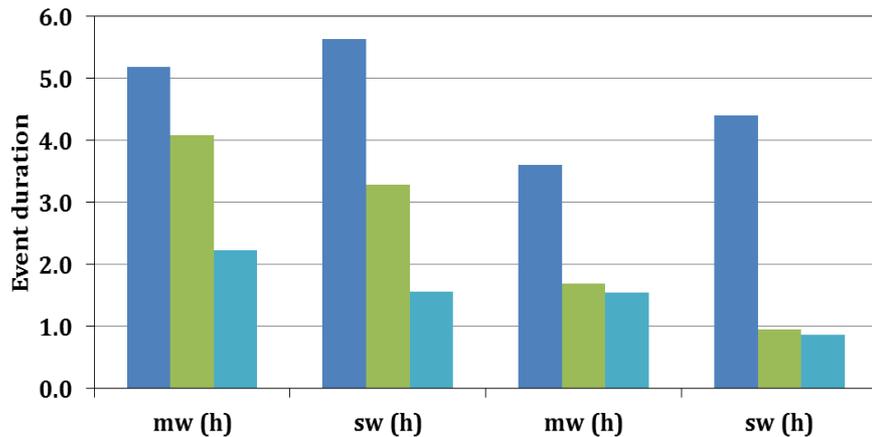
June

15. Time-related properties of storms



Mean and standard deviation of dry intervals duration (left: January; right: June)

Historical vs. simulated probability dry for different temporal scales (January)

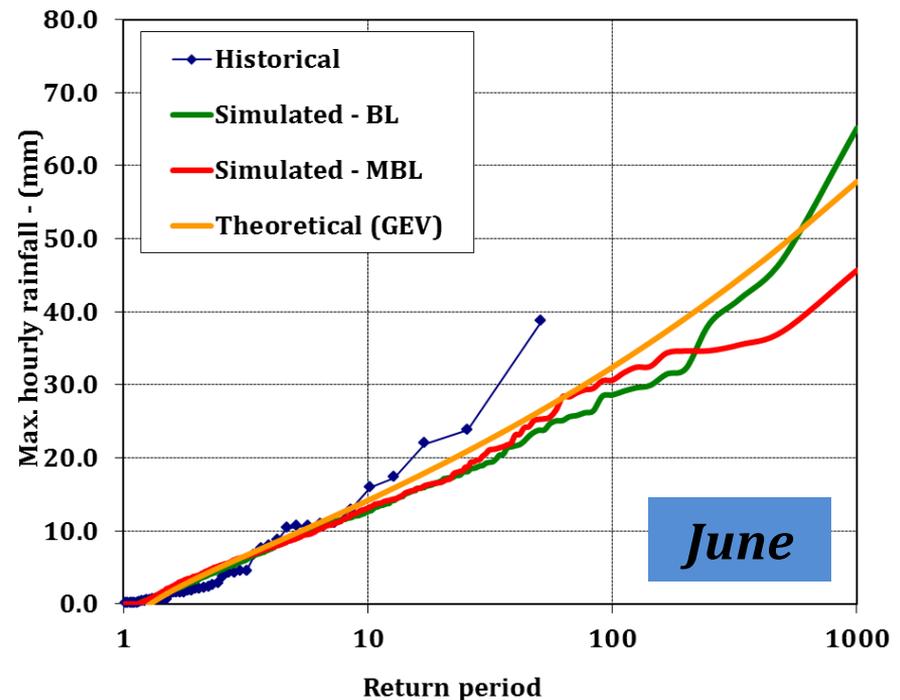
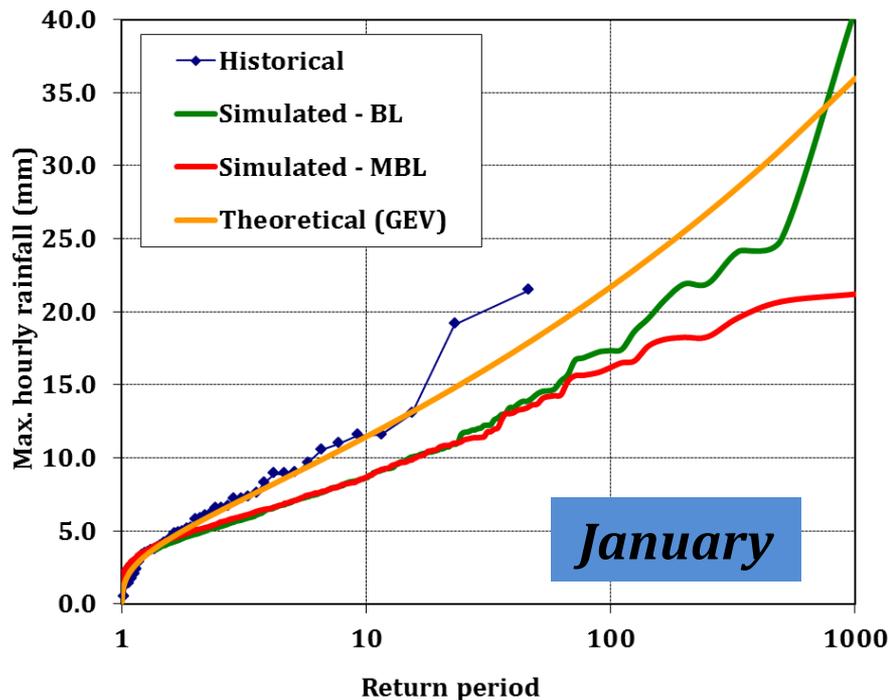


Mean and standard deviation of duration of rainfall events (left: January; right: June)

Historical vs. simulated probability dry for different temporal scales (June)

16. Reproduction of extremes

- ❑ To assess the statistical behavior of the extreme rainfall, we compare the empirical CDFs of the annual maxima of historical and simulated hourly data (sorted maxima of each hydrological year).
- ❑ The empirical CDFs are also compared to a theoretical statistical model, i.e. the GEV distribution, which is fitted to historical maxima; the deviations are quite large for January storms, in contrast to June, for which statistical predictions are close to the GEV model.



17. Conclusions

- ❑ The calibration of model parameters against different set of statistics lead to different parameter values and model performance, in terms of preserving the statistical characteristics that are not directly involved in objective function, especially in the case of the modified BL model.
- ❑ The seasonal variability of model parameters does not allow inferring about their physical interpretation.
- ❑ The analysis shows that both models reproduce the statistical characteristics that are implicitly involved in calibration process (i.e. hourly and daily scale), having poor performance in the reproduction of statistics at the 6-h and 12-h time scales.
- ❑ Both versions of the BL model fail to reproduce the significant variability of rainfall events, due to the overclustering of pulses, which also results to over-estimation of probability dry, at the hourly and daily time scales.
- ❑ Further improvement on the model structure is required to ensure the reproduction of extremes, which is of key importance in flood studies.

18. References

- ❑ Efstratiadis, A., and D. Koutsoyiannis, An evolutionary annealing-simplex algorithm for global optimisation of water resource systems, *Proceedings of 5th International Conference on Hydroinformatics*, Cardiff, UK, 1423–1428, IWA, 2002.
- ❑ Kossieris, P., *A computer program for temporal stochastic disaggregation of a fine-scale rainfall on R environment*, Diploma thesis, 224 p., Department of Water Resources & Environmental Engineering, National Technical University of Athens, Athens, 2011.
- ❑ Kossieris, P., *Adaptation of evolutionary annealing-simplex algorithm for optimization of stochastic objective functions in water resource problems*, Postgraduate Thesis, 209 p., Department of Water Resources & Environmental Engineering, National Technical University of Athens, 2013.
- ❑ Kossieris, P., D. Koutsoyiannis, C. Onof, H. Tyrallis, and A. Efstratiadis, HyetosR: An R package for temporal stochastic simulation of rainfall at fine time scales, *EGU General Assembly 2012, Geophysical Research Abstracts, Vol. 14*, Vienna, 11718, European Geosciences Union, 2012.
- ❑ Koutsoyiannis, D., and C. Onof, A computer program for temporal rainfall disaggregation using adjusting procedures (HYETOS), *XXV General Assembly of European Geophysical Society, Nice, Geophysical Research Abstracts, 2*, 2000.
- ❑ Rodriguez-Iturbe I., D.R. Cox, and V. Isham, Some models for rainfall based on stochastic point processes, *Proc. R. Soc. Lond.*, A410, 269-288, 1987.
- ❑ Rodriguez-Iturbe I., D.R. Cox, and V. Isham, A point process model for rainfall: Further developments, *Proc. R. Soc. Lond.*, A417, 283-298, 1988.
- ❑ Tsoukalas, I., P. Kossieris, A. Efstratiadis, and C. Makropoulos, Surrogate-enhanced evolutionary annealing simplex algorithm for effective and efficient optimization of water resources problems on a budget, *Environmental Modelling & Software*, 2015 (submitted).

Acknowledgement

This research has been financed by the European Union (European Social Fund – ESF) and Greek national funds through the Operational Program “Education and Lifelong Learning” of the National Strategic Reference Framework (NSRF) – Research Funding Program: ARISTEIA II: Reinforcement of the interdisciplinary and/ or inter-institutional research and innovation (CRESSENDO project; grant number 5145).

**The presentation is available online at
<http://www.itia.ntua.gr/1526/>**