Open access • Journal Article • DOI:10.1002/HYP.7867

Are stochastic point rainfall models able to preserve extreme flood statistics — Source link

Niko E. C. Verhoest, S. Vandenberghe, Pieter Cabus, Christian Onof ...+2 more authors

Institutions: Ghent University, Environment Agency, Imperial College London, ParisTech

Published on: 15 Nov 2010 - Hydrological Processes (Wiley)

Topics: Flood myth and Precipitation

Are stochastic point rainfall models able to preserve extreme flood statistics?

Niko E.C. Verhoest[1,*], S. Vandenberghe[1], P. Cabus[2], C. Onof[3], T. Meca-Figueras[3], S. Jameleddine[4]

[1]Laboratory of Hydrology and Water Management, Ghent University, Coupure links 653, B-9000 Ghent, Belgium
[2]VMM (Flemish Environmental Agency), Sluizenweg 2, B-9050 Gentbrugge, Belgium
[3]Department of Civil and Environmental Engineering, Imperial College London, Skempton Building, London SW72AZ, United Kingdom
[4]Ecole des Ponts Paris Tech, 6-8 avenue Blaise-Pascal, Cité Descartes, 77455 Champs-sur-Marne, Marne-la-Vallée cedex 2, France
[*]Corresponding author

On November 26, 2007, the European Directive on the Assessment and Management of Flood Risks entered into force requiring that all European Member States identify areas at risk of flooding. For these areas, flood risk maps need to be drawn by 2013 and flood risk management plans are to be developed by 2015, where flood risk refers to "*the combination of the probability of a flood event and of the potential adverse consequences of human health, the environment, cultural heritage and economic activity associated with a flood event*" (Directive 2007/60/EC, 2007). An important aspect within the exercises to be carried out by each Member State will thus be the correct assessment of the return periods of extreme flood events.

A conventional approach, still frequently used, is to estimate flood discharge for individual precipitation events of particular interest (e.g. Institute of Hydrology, 1999), these being a significant historical rainfall event or a simulated design storm with given statistical properties (Wheater, 2002). The disadvantage of such an approach is that the antecedent wetness state of the catchment is generally not properly accounted for. This antecedent condition, however, determines the magnitude of Dunne runoff production and therefore the fluvial response to each precipitation event, which means that the return period of a flood event does not generally correspond to that of the causing storm event. This is also demonstrated in Figure 1, from which it can be seen that extreme discharge events often result from less extreme rainfall which must have fallen on a wet catchment. It follows that the conventional approach cannot be used to provide flood frequency maps needed as input for flood risk maps. Continuous discharge modelling using long term rainfall records overcomes the problem mentioned above, and a frequency analysis of the obtained discharge time series enables the calculation of the requested probability of flood events. Unfortunately, this approach is limited by the length of the available rainfall time series which hampers the accurate modelling of very low frequency flood events. To circumvent this, one could consider using very long stochastically modelled rainfall time series for the continuous simulation of streamflow (Boughton and Droop, 2003).

Rainfall modelling can generally be classified into four categories (Onof et al., 2000): (1) meteorological models involving complex sets of differential equations representing the physical processes controlling precipitation and other weather variables; (2) stochastic multi-scale models describing the spatial evolution of the rainfall process independently of scale; (3) statistical models which can allow for the modelling of trends; and (4) stochastic process models which, although they make simple assumptions with respect to the physical processes, enable the description of the hierarchical structure of the rainfall process with a minimal set of model parameters. The latter stochastic process models, more specifically point-scale Bartlett-Lewis rectangular pulse models, are the focus of this commentary.

INSERT FIGURE 1 HERE

Rainfall modelling using Bartlett-Lewis rectangular pulse models

The Bartlett-Lewis rectangular pulse model was first developed by Rodriguez-Iturbe et al. (1987). This model showed some shortcomings with respect to preserving the zero depth probabilities. To solve this, a modified version of the model (i.e. the Modified Bartlett-Lewis (MBL) model) was introduced by Rodriguez-Iturbe et al. (1988). Further developments of the model structure were introduced by Onof and Wheater (1994) in order to improve the reproduction of extreme rainfall events (further referred to as the Modified Bartlett-Lewis Gamma (MBLG) model). In all of these models, storms are assumed to arrive according to a Poisson process (with rate λ). Within each storm, rectangular cells, which may be overlapping, arrive according to another Poisson process (rate β). The duration of the activity of the corresponding storm is modelled by an exponential distribution with parameter γ. The depth of a cell follows an exponential distribution (parameter $1/\mu_x$) and its duration is modelled from an exponential distribution with parameter η. In both modified versions of the Bartlett-Lewis model, η is sampled for each storm from a two-parameter gamma distribution with shape parameter α and scale parameter $1/\nu$. β and γ are scaled proportionally to the cell duration through the dimensionless parameters κ (=β/η) and ϕ (=γ/η). For the MBLG, the parameter μ_x is furthermore modelled through a gamma distribution having a shape parameter p and scale parameter δ. The MBL is thus defined by 6 parameters $\{\lambda,\mu_x,\alpha,\nu,\kappa,\phi\}$, whereas the MBLG is characterized by 7 parameters $\{\lambda,\alpha,\nu,\kappa,\phi,p,\delta\}$. Both models are generally fitted through minimizing the error between, on the one hand, analytically calculated moments and covariances of the depth distribution, and zero depth probabilities, all at different aggregation levels, and on the other hand, the corresponding observed values of these statistics.

Several empirical studies have been performed in which Bartlett-Lewis models were fitted to rainfall time series in Great Britain (Onof and Wheater, 1993, Glasbey et al., 1995, Cameron et al., 2000), Ireland (Khaliq and Cunnane, 1996), Belgium (Verhoest et al., 1997), South Africa (Smithers et al., 2002), Austria (Bogner et al., 2001), the Netherlands, Gibraltar, Italy (Marani and Zanetti, 2007), Australia (Gyasi-Agyei and Willgoose, 1999) and the United States (Velghe et al., 1994, Marani and Zanetti, 2007). Generally, these studies report a good performance of the model with respect to simulating the first and second order statistics of rainfall depth at different levels of aggregation. The modified versions of the Bartlett-Lewis model seem to preserve the zero depth probabilities although a too severe clustering of rain events was observed (Verhoest et al. 1997, Vandenberghe et al. 2010b). With respect to the reproduction of extreme values, it was found that the modified Bartlett-Lewis models generally underestimate the extreme values, especially for lower aggregation levels (Verhoest et al., 1997, Cameron et al., 2000) and for return periods greater than the length of the data set (Onof and Wheater, 1993). Based on a modelling study with Belgian data, the MBLG demonstrated similar problems, even though it was designed to improve the reproduction of extreme events. Cowpertwait (1998) attributed this shortcoming of the modelling exercises to the calibration procedure in which higher-order properties were not included in the fitting procedure.

In the case study discussed below, MBL and MBLG models fitted against Belgian data (observed at Uccle), as described in Verhoest et al. (1997), are used. A detailed analysis of their first and second order statistics, the internal storm structure, the dependence between storm characteristics (duration, intensity and volume) and extreme value representation can be found in Verhoest et al. (1997) and Vandenberghe et al. (2010b). Table 1 presents the first to fifth order non-centered moments of hourly rainfall data, calculated for the observed 105 year rainfall time series at Uccle and for both 1001 year modelled time series. From this Table, it can be seen that both models preserve the first two moments fairly well, but underestimate the higher moments.

The deviations observed in the Table are partly due to the fact that only first and second order moments (at 10 minute and 24 hour aggregation levels) were used in the calibration of both models. Including the higher order moments in the calibration could have solved this problem. Unfortunately, only the analytical expressions for the third-order moment of the original non-modified Bartlett-Lewis model are available (Wheater et al., 2006, p.419). Analytical expressions for the third-order moments, valid for the modified

Bartlett-Lewis models, have yet not been published (Onof et al., in preparation). Note that the calculation of the analytical higher-order moments is not tractable.

With respect to the preservation of the extreme rainfall statistics, it can be seen from Figure 2 that both MBL and MBLG models underestimate the extreme events at an hourly time scale, but overestimate the extreme events at a 24 hour time scale. As mentioned before, this problem was already identified in the literature.

INSERT FIGURE 2A and 2B HERE

Flood probability modelling

Flood probability maps can be obtained from 2-dimensional hydraulic simulations which are forced by extreme discharge events at the upper boundary. Such boundary conditions are generally obtained from observations, or from hydrological model simulations. In the latter case, simple (generally lumped) hydrological models, such as the Probability Distributed Model (PDM, Moore, 2007), are often used by water managers. Of course, in order to have reliable flood probability maps, the extreme discharge events used should preserve the extreme flood statistics at the upstream boundary.

In order to illustrate the applicability of Bartlett-Lewis-based rainfall time series for extreme discharge modelling, the PDM is applied to a Flemish watershed (Grote Nete catchment, see Cabus (2008) for a detailed analysis of the PDM applied to several Flemish catchments). This conceptual model simulates river discharge through coupling of a non-linear reservoir (representing the soil moisture storage) with linear reservoirs (representing subsurface and surface storage). In the exercise below, this model is forced by 105 year hourly rainfall observed at Uccle and 1001 year MBL- and MBLG-simulated rainfall data.

Figure 3 shows the extreme value analysis based on yearly modelled maximal discharge. The discharge extremes calculated from the observed Uccle rainfall clearly demonstrate a Fisher-Tippet Type I extreme value or Gumbel distribution, whereas both modelled rainfall time series follow a Type II or Fréchet distribution. Both rainfall models result in too high a probability of occurrence for extreme discharge events. For instance, a 50-year extreme flood event, as modelled with the observed rainfall, is assigned a 20-year return period when modelled using the MBLG rainfall time series. If the approach of continuous modelling, in which these Bartlett-Lewis modelled rainfall series are applied, were used to develop flood risk maps, areas which are too large would be assigned too high a risk.

INSERT FIGURE 3 HERE

Pinpointing the problem

As can also be inferred from Figure 1, the reason for extreme discharge events should not always be sought in the occurrence of extreme rainfall events. Improving the models with respect to reproducing the extreme rainfall therefore should not necessarily have a positive impact on extreme discharge modelling. The antecedent moisture condition of the catchment greatly determines the rainfall-runoff process, indicating that the sequence of historical rainfall events prior to the flood should also be looked at. When studying the discharge as well as the rainfall time series in a time frame around each of the extreme flood events, some peculiar phenomena are often observed (as demonstrated for one flood event in Figure 4): some very long cells of moderate to high rainfall intensities were observed which preceded or caused the flood event. Note that this will often lead to extreme events at coarser time scales, e.g. at the daily time step: when analysing the rainfall events causing the extremes at the daily scale, the overestimations of the Bartlett-Lewis models can be attributed to the occurrence of such unrealistic rainfall cells, whereas, at the hourly time scale, the annual maxima do not generally result from these model shortcomings.

The occurrence of these unrealistic rainfall cells results from the fact that the η parameter, which is randomly drawn from a gamma distribution, was assigned an extremely low value (Wheater et al. 2006). Consequently, the probability of randomly sampling a cell of very long duration is very high (its expected value is η^{-1}). Through the scaling parameter ϕ, the expected duration of the storm activity, i.e. $(\eta\phi)^{-1}$, becomes very large. Within this storm, however, rainfall cells arrive with a low expected rate (i.e. $\kappa\eta$). If a moderate to high cell intensity, independently drawn from another exponential distribution, is assigned to one of these long-lasting cells, an unrealistic rainfall cell is generated. Although these cell intensities are not exceptional, and do not therefore lead to any hourly extremes, their long duration leads to distorting the extremes at coarser time-steps such as daily aggregation levels. Nonetheless, these rare events are responsible for the overestimation of the extreme floods.

This problem is also found (although to a lesser extent) when the skewness is included among the statistics used to fit the model (analytical moments will be made available in Onof et al. (in preparation)). Both MBL and MBLG models were recalibrated including the third order moment in the cost function to be minimized, and the resulting models are referred to as MBL_3 and MBLG_3. Table 1 summarizes the statistics obtained for these models. It is found that, especially for the MBLG_3 model, the third and higher order moments are better represented than before. As can be seen from Figure 2, lower extreme values are observed, leading here to a more severe underestimation at the hourly aggregation level than was originally the case with the MBL and MBLG models is obtained, whereas at the daily scale, the overestimation of the extremes is reduced somewhat. That the results are not as good as those obtained by Cowpertwait (1998) for the Neyman-Scott model when skewness was used in the calibration, is a consequence of a problem that has been overlooked in the calculation of the moments of the MBL/MBLG and is investigated by Onof et al. (in preparation).

In Figure 5, an extraction of an MBLG_3-modelled rainfall time series is displayed. As can be seen, the simulated series is still hampered with the unrealistic simulation of long rain cells. When the time series are used to force the PDM, overestimations of the extreme discharges, although lesser in extent, are again observed, as is demonstrated in Figure 3.

INSERT FIGURE 4 HERE

INSERT FIGURE 5 HERE

INSERT TABLE 1 HERE

Future improvements?

Several options exist to prevent the occurrence of these extreme rainfall cells. One way to solve the problem is through incorporating a dependence structure between the cell duration and its intensity. Evin and Favre (2008) suggested modelling this dependence using copulas. Their reasoning was based on the negative dependence between storm duration and intensity as observed by De Michele and Salvadori (2003), which was also present in the Uccle data (Vandenberghe et al., 2010a). Unfortunately, the impact of introducing such dependence in the model was not analysed with respect to extreme rainfall modelling, nor has it been assessed in a rainfall-runoff modelling framework. Improving the Bartlett-Lewis model structure through implementing a copula would be worth testing, and its merit with respect to extreme rainfall modelling and the preservation of extreme discharge statistics should be investigated in detail.

An alternative solution to the problem could be to restrict η to values larger than a predefined threshold. Wheater et al. (2006) implemented a “restricted eta version” applying a threshold of 0.1 and found in some preliminary results that the problem of the generation of extremely large and therefore unrealistic rainfall cells was indeed largely resolved. To assess the impact of such restriction approach on the extreme discharge simulations, all parameter values as calibrated in Verhoest et al. (1997) were maintained in both MBL and MBLG models, and η was prevented from having values less than 0.9 (for η = 0.9, 99.5% of all generated cells have a duration less than 6 hours) instead of 0.1 (as this restriction still results in too many long lasting cells, i.e. at η=0.1, almost 10% of the cells last more than 24 hours). Figure 3 reveals that truncating the gamma distribution for η to values larger than 0.9 has a positive effect on the simulation of the extreme discharge events: the modelled extreme discharge now almost follows the observed Gumbel distribution. This intervention in the model does not, however, seem to have a large impact on the rainfall statistics (see Table 1): generally lower values for all moments are obtained. With respect to the modelling of extreme rainfall, an improvement at the daily scale is found (Figure 2b); yet, at the hourly aggregation level, large underestimations remain (Figure 2a). However, the restricted models used were not optimized, but rather, the exercise performed was intended to demonstrate that the shortcoming of the models for preserving extreme flood events can almost completely be assigned to the generation of unrealistic rainfall cells, and that through a simple intervention in the model, this inadequacy can be eliminated. Further research should focus on recalibrating the restricted models, in which the threshold value for η is included as an additional parameter. Therefore, analytical expressions for the different moments, covariances and zero depth probability will be derived (Onof et al., in preparation) and more advanced calibration methods, which may include multi-objective optimizations of moments and extreme behaviour, could be applied.

Conclusion

In our opinion, current research with respect to stochastic rainfall modelling is still too focussed on the reproduction of rainfall time series, and would benefit from examining the ability of these models to reproduce extreme discharge events when combined with a rainfall-runoff model. Because of the filtering effect of the non-linear transformation, the adequate reproduction of rainfall statistics at a range of time scales is relevant to the quality of the generated streamflows.

On the basis of the study reported here, a restriction should be put on the length of the individual rain cells. This could be obtained by restricting the value of η to values larger than a predefined threshold value, as suggested by Wheater et al. (2006). Preliminary results, obtained with a non-optimized model, show promising results, but further work is needed to calibrate the model with the threshold as an additional parameter. Alternatively, a copula-based dependence structure between cell durations and intensities could be examined for its ability to reproduce the extreme behaviour of rainfall and discharge.

Once this shortcoming of current Bartlett-Lewis rectangular pulse models has been solved, these models possess the potential for generating long time series of rainfall which can be used as input to hydrologic and hydraulic models for flood probability mapping, making them very suitable for use in flood risk mapping as required by the European Commission. To further optimize their applicability in this respect, it is worth exploring whether including extreme statistics of both rainfall (Wheater et al., 2006) and modelled discharge in the calibration of the models could improve their performance for hydrological applications. This would involve looking beyond the analytical expressions of descriptive statistics to a Monte Carlo based approach to model fitting.

Acknowledgements

The authors would like to thank the Royal Meteorological Institute (RMI) of Belgium for providing the extensive data set of Uccle rainfall. The second author is a doctoral research fellow of the Research Foundation Flanders (FWO).

References

Bogner, K., Konency, F., Nachtnebel, H.P., Onof, C. 2001. Simulation of rainfall with different temporal resolutions by stochastic pulse models", in 'Scaling problems in hydrology', eds. D. Gutknecht, M. Hantel & H.P. Nachtnebel, National Committee of the International Hydrological Programme, Austrian Academy of Sciences, Vienna: 109-122

Boughton W, Droop O. 2003. Continuous simulation for design flood estimation – a review. Environmental Modelling & Software 18(4):309-318.

Cabus P. 2008. River flow prediction through rainfall-runoff modelling with a probability-distributed model (PDM) in Flanders, Belgium. Agricultural Water Management 95(7):859-868.

Cameron D, Beven K, Tawn J. 2000. An evaluation of three stochastic rainfall models. Journal of Hydrology, 228(1-2):130-149.

Cowpertwait PSP. 1998. A Poisson-cluster model of rainfall: high-order moments and extreme values. Proc. R. Soc. Lond. A 454:885-898.

De Michele C, Salvadori G. 2003. A generalized Pareto intensity-duration model of storm rainfall exploiting 2-Copulas. J. Geophys. Res. 108(D2):4067, doi:10.1029/2002JD002534.

Directive 2007/60/EC. 2007. Directive 2007/60/EC of the European Parliament and of the Council of 23 October 2007 on the assessment and management of flood risks. Official Journal of the European Union, L288/27.

Evin G, Favre AC. 2008. A new rainfall model based on the Neyman-Scott process using cubic copulas. Water Resour. Res. 44:W03433, doi:10.1029/2007WR006054.

Glasbey C, Cooper G, McGechan MB. 1995. Disaggregation of daily rainfall by conditional simulation from a point process model. J. Hydrol. 165(1-4):1-9.

Gyasi-Agyei Y, Willgoose GR. 1999. Generalisation of a hybrid model for point rainfall. J. Hydrol., 219(3-4): 218-224.

Institute of Hydrology 1999. Flood estimation handbook. Institute of Hydrology. Wallingford, Oxfordshire United Kingdom.

Khaliq MN, Cunnane C. 1996. Modelling point rainfall occurrences with the modified Bartlett-Lewis rectangular pulses model. J. Hydrol. 180(1-4):109-138.

Marani, M., Zanetti, S. (2007) Downscaling rainfall temporal variability, Water Resour. Res. 43, doi:10.1029/2006WR005505

Moore RJ. 2007. The PDM rainfall-runoff model. Hydrol. Earth Syst. Sci. 11(1):483-499.

Onof C, Chandler RE, Kakou A, Northrop P, Weather HS, Isham V. 2000. Rainfall modelling using Poisson-cluster processes: a review of developments, Stochastic Environmental Research and Risk Assessment 14:384-411.

Onof C, Wheater HS. 1993. Modelling of British rainfall using a random parameter Bartlett-Lewis Rectangular Pulse model. J. Hydrol. 149(1-4):67-95.

Onof C, Wheater HS. 1994. Improvements to the modelling of British rainfall using a modified random parameter Bartlett-Lewis rectangular pulse model. J. Hydrol. 157(1-4):177-195.

Onof C, Kaczmarska J, Meca-Figueras T, Hege L, Isham V. In preparation. Modelling rainfall with a Bartlett-Lewis process: third-order moments, proportion dry, and a truncated random parameter version.

Rodriguez-Iturbe I, Cox DR, Isham V. 1987a. Some models for rainfall based on stochastic point processes. Proc. Roy. Soc. Lond. A 410:269-288.

Rodriguez-Iturbe I, Cox DR, Isham V. 1988. A point process for rainfall: further developments. Proc. Roy. Soc. Lond. A 417:283-298.

Smithers JC, Pegram GGS, Schultze RE. 2002. Design rainfall estimation in South Africa using Bartlett-Lewis rectangular pulse rainfall models. J. Hydrol. 258(1-4):83-99.

Vandenberghe S, Verhoest NEC, De Baets B. 2010a. Fitting bivariate copulas to the dependence structure between storm characteristics: a detailed analysis based on 105 year 10 min rainfall, Water Resour. Res. 46:W01512, doi:10.1029/2009WR007857.

Vandenberghe S, Verhoest NEC, Onof C, De Baets B. 2010b. Evaluation of Bartlett-Lewis rainfall models through a comparative copula-based bivariate frequency analysis of observed and simulated rainfall time series. Water Resour. Res. Conditionally accepted.

Velghe T, Troch PA, De Troch FP, Van de Velde J. 1994.Evaluation of cluster-based rectangular pulses point process models for rainfall. Water Resour. Res. 30(10):2847-2857.

Verhoest N, Troch PA, De Troch FP. 1997. On the applicability of Bartlett-Lewis rectangular pulses models in the modeling of design storms at a point. J. Hydrol. 203(1-4):108-120.

Wheater HS. 2002. Progress in and prospects for fluvial flood modelling. Phil. Trans. R. Soc. Lond. A 360:14019-1431.

Wheater HS, Isham VS, Chandler RE, Onof CJ, Stewart EJ. 2006. Improved methods for national spatial-temporal rainfall and evaporation modelling for BSM, R&D Technical Report F2105/TR, Department for Environment, Food and Rural Affairs, London, 497p., http://randd.defra.gov.uk/Document.aspx?Document=FD2105_6227_PR.pdf.

Table 1. First to fifth order moments of the hourly precipitation time series and corresponding modelled discharge time series for 105 year observed rainfall at Uccle, and 1001 year MBL and MBLG modelled rainfall using non-restricted and restricted models.

Data series used	mean (mm/h)	variance (mm^2/h^2)	3rd moment (mm^3/h^3)	4th moment (mm^4/h^4)	5th moment (mm^5/h^5)
Precipitation					
Observed	0.0919	0.2220	1.5837	24.8835	594.2728
MBL	0.0925	0.2092	1.2332	17.0239	427.6917
MBLG	0.0921	0.2106	1.2142	13.3704	212.5212
MBL_3	0.0923	0.2315	1.2951	13.0503	192.4415
MBLG_3	0.0916	0.2378	1.4592	16.7188	280.4437
Restricted MBL	0.0899	0.1980	1.0974	12.8870	243.8037
Restricted MBLG	0.0907	0.1990	1.0870	11.6286	184.7337
Modelled discharge per unit of catchment area					
Observed	0.0338	1.41E-03	2.42E-04	8.15E-05	3.70E-05
MBL	0.0342	1.94E-03	2.10E-03	7.51E-03	3.61E-02
MBLG	0.0341	4.55E-03	3.04E-02	3.33E-01	3.98E+00
MBL_3	0.0340	1.42E-03	3.29E-04	2.23E-04	2.86E-04
MBLG_3	0.0336	1.42E-03	3.71E-04	2.93E-04	4.04E-04
Restricted MBL	0.0322	1.14E-03	1.90E-04	6.70E-05	3.59E-05
Restricted MBLG	0.0329	1.21E-03	2.22E-04	9.75E-05	7.13E-05

List of figures