

Response to reviewer comments: Anonymous Referee #2

GENERAL COMMENTS 1)

In this study as a part of the assessment of statistical characteristics of point rainfall, we have fitted different probability distributions to simulate daily rainfall amounts and we evaluated the performance of various probability distributions to reproduce the full range of daily rainfall. We have included the discussion on the limitation of the hybrid gamma-GP distribution due to its fitting procedure to the revised manuscript in section 4.1.2. As per the reviewer's suggestion, we have now included mixed exponential (Wilks, 1999) and hybrid of exponential-Generalized Pareto (GP) (Li et al., 2012) distribution to the revised manuscript.

GENERAL COMMENTS 2)

We also agree with the reviewer that the spatial dependence structure of rainfall at different temporal resolutions is important for rainfall modelling and it has significant impact on the rainfall runoff modelling. We have added an analysis of the spatial dependence structure of the observed rainfall at different temporal resolutions in the revised manuscript at section 4.

Response to specific comments:

1. Reviewer is curious to know about the peculiarities of the Onkaparinga catchment for selecting as a study area for rainfall characteristics assessment. We have already mentioned that this is a relatively small catchment with very high spatial variability in rainfall. This catchment is also important for its valuable contribution to the city of Adelaide's water supply and for meeting local irrigation demand. The Onkaparinga catchment is hydrologically very well instrumented, partly because of its importance as a water supply catchment and partly because it includes the Willunga Basin Super Science Site, which funded by the Australian Commonwealth Government's Super Science program for the development of scientific infrastructure.

We have now included additional text in the revised manuscript describing why Onkparianga catchment was selected for this study.

2. We have added the CDF of the gamma and GP distribution in the revised manuscript.

3. Willmott (1981) first proposed the index of agreement (d) to overcome the insensitivity of Nash-Sutcliffe efficiency (E) and coefficient of determination (R^2) to differences in the observed and model simulated means and variances, which is given by

$$d = 1.0 - \frac{\sum_{i=1}^N (O_i - P_i)^2}{\sum_{i=1}^N (|P_i - \bar{O}| + |O_i - \bar{O}|)^2} = 1 - N \frac{MSE}{PE}$$

The index of agreement is the ratio of the mean square error and the potential error (PE) multiplied by N (no. of observation) and then subtracted from one (Willmott, 1984). The index of agreement varies from 0 to 1 with higher index values indicating that the modelled values P_i have better agreement with the observations, O_i . Although the index of agreement provides some improvement over the coefficient of determination, it is still sensitive to extreme values due to the square differences in the mean square error in the numerator. Application of the index of agreement shows that the relatively high values of d may be obtained even for a poor model fit (Willmott, 1984). The presence of outliers in the dataset may lead to relatively higher values of d due to the squaring of the difference term (Willmott, 1981). In order to overcome this limitation, Legates and McCabe Jr (1999) introduced a modified index of agreement followed by a generic form of index of agreement proposed by Willmott (1984) and this is defined as:

$$d = 1.0 - \frac{\sum_{i=1}^N |O_i - P_i|}{\sum_{i=1}^N (|P_i - \bar{O}| + |O_i - \bar{O}|)}$$

The advantage of the modified index of agreement is that the errors and differences are given their appropriate weighting, and are not inflated by their squared values. The modified index of agreement also varies from 0 to 1 with higher values indicating a better fit of the model.

4. We have already mentioned in Section 3.4 that the PCI were introduced by Oliver (1980) and then modified by De Luis et al. (2000). Further details on PCI are given in De Luis et al. (2011) and De Luis et al. (2010).

5. In this study we only modelled the daily rainfall amount for the observed wet days using the gamma, exponential, Weibull and hybrid distributions. Daily rainfall modelling generally follows a two step approach. First, the occurrence of rainfall in any day is identified and second, the rainfall amount is modelled for that day. With reference to the errors involved in the amount model, this is largely influenced by the occurrence model, which results in bias in the modelled values as compared to the observed values. For example, if the occurrence model identifies a day as a dry day although it is a wet day in the observed data, the amount model does not model rainfall on that day. Sometimes the amount model generates rainfall in a day which is dry in the observed data and vice versa due to the limitation of the occurrence model. Therefore we only considered modelling rainfall amounts in observed rainy days. In order to assess the performance of the model in terms of reproducing different rainfall statistics, we have estimated the rainfall for every observed wet day using the probability distribution. A day is considered as wet day if it has a daily rainfall amount greater than 0.5 mm. For any wet day, the estimated model parameters have been used to generate the rainfall for that day using the particular probability distribution model. In this way the amount model is kept independent of the influence of the occurrence model so that the performance of the distribution model can be examined separately.

6. We have mentioned in Section 4 in the revised manuscript about the consequence of central limit theorem in the discussion of the fact that the annual and seasonal rainfalls show lower skewness and kurtosis values compare to those of daily rainfall.

7. The shape and the scale parameters of the gamma distribution are not independent. The product of the estimates of shape and scale is equal to the mean of the non-zero rainfall observations. The variance of the gamma distribution is the estimated shape parameter multiplied by the square of the scale parameter. So, in other words, the square root of the shape parameter is approximately equal to the mean divided by the variance. A larger shape parameter value within a low mean rainfall area will have low variance. A smaller shape parameter value in an area with high mean rainfall will indicate high variance. It is apparent that as the shape and scale parameters are related to each other through the mean rainfall, the area with minimal rainfall amounts is described by either a relatively large shape or scale parameter but not large values of both parameters. In this study we have found that the minimal rainfall can be described by the larger shape parameter. The term shape-dominant rainfall refers to the locations where larger shape parameters exist and the term scale-dominated rainfall refers to the locations with larger scale parameters. A shape-dominated regime describes a pattern where the rainfall tends to be symmetrically distributed, indicating that drier-than-average events are as common as wetter-than-average events. On the other hand scale-dominated rainfall describes locations where the variance is quite large in comparison to the mean. We have now added this explanation to the revised manuscript.

8. We tried to mention here that in the case of the normal distribution, a single parameter such as the mean or standard deviation can be used directly to understand the properties of distribution. This is not so straightforward in the case of the gamma distribution since both the shape and scale parameters are needed to describe the characteristics of the distribution. We have now rewritten this in the revised manuscript as:

“Interpretation of the gamma distribution is not as straightforward as the normal distribution where any single parameter such as mean or standard deviation can be directly used to understand the characteristics of the distribution.”

9. The skewness and kurtosis estimated in Table 3 are not the same as the skewness and kurtosis estimated by the formula $2/\sqrt{\text{shape}}$ and $6/\text{shape}$ using the shape parameter of the gamma distribution. This is because the parameters (shape and scale) (Fig. 3) were estimated by the MLE after fitting a gamma distribution to the daily non-zero rainfall whereas the skewness and kurtosis presented in Table 3 were estimated considering the full rainfall series.

10. Selection of a threshold in the Generalized Pareto (GP) distribution is crucial for its performance. Several studies have been conducted for the selection of an optimum threshold. Several thresholds were tried and the value was finally optimized by the help of goodness of fit statistics. The literature shows that goodness of fit statistics based on the cumulative distribution function and probability distribution function have often been used to find the best fit distribution. For example, Choulakian and Stephens (2001) used a trial and error method to estimate the optimum threshold for

the GP distribution. They fitted a GP distribution considering a threshold and then assessed the performance of the distribution by checking the goodness of fit statistics including the Cramér-von Mises statistics (W^2) and the Anderson – Darling statistics (AD^2). The threshold was then increased successively by the value of the smallest order statistics until the significant statistics (p value) of the W^2 and AD^2 exceeded 10%. An optimum threshold for the GP distribution was selected based on the robust estimation of the distribution parameter by Dupuis (1999) In this study we have used the goodness of fit statistics to compare the fit between the observed and the modelled rainfall. We believe that as our focus is to model the rainfall amount, examining the performance of fit by comparing the observed and modelled values will give more confidence on the selection of the optimal threshold.

In the hybrid distribution the selection of the threshold should not be too small nor too large (Li et al., 2012). An optimum threshold would be around the point where the gamma distribution starts to lose its performance in terms of restimulating the rainfall. We have selected a threshold, then simulated the rainfall and checked the performance of the model by looking at different percentiles (for example 5th, 10th, 20th and so on) of the simulated rainfall series by using goodness of fit statistics such as the coefficient of efficiency (E) and the index of agreement (d). This goodness of fit approach is widely used for assessing the performance of models in hydro-meteorology (Krause et al., 2005; Legates and McCabe Jr, 1999). When the fitting performance of the gamma and GP distribution model is compared for the different percentiles, it can be easily identified at which percentile the performance of the gamma distribution starts to deteriorate compared to the GP distribution. Once this point (percentile) is selected then this percentile rainfall can be used as an optimum threshold for that time series. So after only one trial the optimum threshold can be identified easily. It was observed in this study that in general a threshold around the 90th percentile of daily rainfall gave the optimum performance for the hybrid model for all rainfall stations in the Onkaparinga catchment. This result also reveals that in general the rainfall up to the 90th percentile is well simulated by the gamma distribution while the GP distribution best fitted the upper percentiles of rainfall (90th to 100th) in the Onkaparinga catchment.

11. We have changed the sentence according to the reviewer's suggestion in the revised manuscript.

12. In this study we focused on assessing the performance of different distribution models to simulate the entire series of rainfall. We evaluated the performance of each distribution model by comparing the observed and simulated rainfall rather than using the cumulative density function or the probability density function. We have applied the widely used goodness of fit statistics such as the coefficient of efficiency (E) and the index of agreement (d) to compare the simulated and observed rainfalls. We have now deleted Table 6 and Fig. 7 from the revised manuscript.

13. In the hybrid (gamma + GP) distribution we have first fitted a gamma distribution for the entire series of the rainfall and then the Generalized Pareto (GP) distribution was fitted for the extreme rainfall greater than a threshold value. When the gamma distribution was fitted to the whole series it overestimated the lower percentiles and underestimated the higher percentiles. For the higher percentiles, the gamma was

replaced by the GP distribution and the differences between the simulated and observed rainfalls for the higher percentiles then reduced remarkably. We have now explained in detail in Section 4.1.2 how this fitting procedure affects the performance of the hybrid distribution when daily rainfall is aggregated to annual and seasonal rainfalls.

14. Fitting a separate distribution model for annual and monthly rainfall is an alternative approach. But when a model is developed to simulate the daily rainfall, generally the model performance is also assessed for the aggregated series (Charles et al., 2004; Fealy and Sweeney, 2007; Furrer and Katz, 2007). In particular, it is usual to check how the daily model simulates the seasonal and inter-annual variation of the rainfall. Moreover, if a daily model can reasonably reproduce the monthly and annual statistics of rainfall then there should be no need to fit separate models for annual and monthly rainfall. This is why we have assessed the model capacity for simulation of monthly and annual total rainfalls.

15. Fig 9. shows the monthly mean variation of the standard deviation and skewness of daily rainfall over the period 1960 to 2010. Standard deviation and skewness of daily rainfall were estimated for each month and for each year over the period of 1960 to 2010, and then the average for each month was estimated separately. We have now explained this in more detail in the revised manuscript.

16. Page 5990, line 20 should have read annual maximum (AM) rainfall. This has been corrected in the revised manuscript.

17. Due to the space limitation we were not able to accommodate all the stations in Figure 10. However, we have selected three stations which are representative of the upstream (distant from the coast), middle and downstream (near the coast) regions of the catchment. We have added additional discussion on the results for the other stations in the revised manuscript.

18. According to the definition of precipitation concentration index (PCI), it shows how the rainfall amount is distributed within a specific period of time. For example, $PCI < 10$ indicates a uniform rainfall concentration which means that the rainfall amount is uniformly distributed over a period of time. On the other hand, higher PCI values indicate higher percentages of total rainfall occurring in only a few rainy days which has the potential to cause floods and/or droughts. So, higher PCI values suggest an increased likelihood of extreme events.

Additional References

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