23rd International Congress on Modelling and Simulation, Canberra, ACT, Australia, 1 to 6 December 2019
mssanz.org.au/modsim2019

Applying rainfall ensembles to explore hydrological uncertainty

N. Kumari [a], **S. C. Acharya** [b], **L. J. Renzullo** [c] **and O. Yetemen** [a]

[a] *School of Engineering, Faculty of Engineering and Built Environment, The University of Newcastle, Callaghan, NSW, Australia.*
[b] *Department of Infrastructure Engineering, The University of Melbourne, Melbourne, Australia*
[c] *Fenner School of Environment and Society, The Australian National University, Australian Capital Territory.*
Email: Nikul.Kumari@uon.edu.au

Abstract: The widespread presence of spatial and temporal variability in rainfall is well known. However, this variability can not be captured by point gauge measurements alone. An accurate representation of this variability is crucial for hydrological and meteorological applications. Precipitation information is an essential input for all hydrological models, but can be especially challenging in regions where no or very few rain gauge stations are established. Moreover, the uncertainties involved in these rainfall inputs are usually not considered or ignored in the hydrological simulations. Uncertainty in precipitation input arising from errors in spatial representation, measurement or estimation accuracy, can create uncertainty in the streamflow estimation. In such cases, the use of high resolution rainfall ensembles can play crucial role in modelling the rainfall-runoff relationships, particularly for high flows or flash floods. This study aims to characterise the hydrological uncertainty involved in the high flow simulations using rainfall-runoff models.

This study focuses on characterising uncertainty in rainfall-runoff model outputs through the application of ensemble precipitation estimates. We demonstrate the results for selected events in the Macleay River Basin using a simple rainfall-runoff model. The basin is situated in the New South Wales (NSW), mid-north coast of Australia and is prone to flash floods. Historically, flooding in the lower Macleay Valley occurs at every 2 or 3 years, and the largest floods have occurrence interval of 100 years. We also explored the response of basin area on this uncertainty and the cascading of this uncertainty from upstream to downstream of the basin.

The GR4H model, which is an hourly implementation of GR4J, is merged with Muskingum Routing in this study. We used GPM (Global Precipitation Mission) precipitation data at 10km x 10km spatial resolution further downscaled to 2km x 2km spatial resolution for three years (2015-2017). Further, radar data along with the GPM precipitation is used to create 50 member ensemble rainfall estimates at 2km x 2km spatial and hourly temporal resolution. In order to analyse the impact of rainfall uncertainty on streamflow we selected some of the high flows events. The three sub-basins having an area between 377-860 km^2 along with the Macleay Basin (~8,000 km^2) is used to run the simulations. Further, we compared and contrasted the runoff generated at the outlet by grid-wise simulations, basin averaged simulation, and simulations from ensemble rainfall as input with the observed streamflow.

The results show that the grid-wise streamflow generation are comparatively better in capturing the peak flow events in the Macleay Basin and sub-basins than the basin-wise streamflow output probably due to the use of the same parameter throughout the simulations, lower averaged streamflow at each sub-basins, and more amount of overall losses at the basin scale. The observed peak flow is within the range of streamflow simulated using ensemble rainfall for all the basins.

The application of interest to this study is the use of ensemble precipitation forecasts to generate ensemble streamflow forecasts. This study shows that the rainfall-runoff modelling with ensemble precipitation inputs can considerably reduce the amount of uncertainty in simulation results, particularly in data-sparce regions.

Keywords: *Precipitation, hydrological uncertainty, rainfall ensembles, streamflow*

1. INTRODUCTION

Every hydrological model that depicts real-world scenarios and processes within, are based on a set of assumptions and thus, subject to various sources of uncertainties. These uncertainties can affect the utilisation of hydrological models in various applications like water resources management, hydrological forecasting, irrigation planning and hydrologic design (Renard et al., 2010; Srivastava et al., 2017; Paul et al., 18). Hence, the uncertainty quantifications in hydrological models understand error charactersitics and their impact on the quality of hydrological model estimates. Though many studies have been conducted that deal with uncertainty in hydrological space (Renard et al., 2010; Beven, 2016), implementing these methods in an appropriate manner is still a challenging task. Among the different sources of uncertainties affecting rainfall-runoff model estimation, the rainfall input is often significant. Precipitation inputs to models, if not a representation of actual rainfall, could results in erroneous and highly uncertain streamflow predictions (Blöschl and Sivapalan, 1995; Bárdossy and Das, 2008; Van Dijk and Renzullo 2010). There have been a number of attempts to describe the errors included in rainfall inputs, but it is complicated due to the various uncertainties involved within (Bardossy and Das, 2008). In addition to the discrepancy in rainfall amount, the uncertainty arising due to the inability of input rainfall data to accurately represent the spatial variability in rainfall is important yet overlooked due to limited measurements.

Enhancement in rainfall estimations via radars, satellite observations (Liu, 2016), and global or regional reanalysis (Acharya et al., 2019b; Beck et al., 2017) have provided vital information on spatio-temporal variability of rainfall at fine spatial scales (~10 kms). These spatial rainfall estimates have potential to improve streamflow simulation because the spatial variability of rainfall is captured better than sparse distribution of gauge measurements. However, in practice, such high-resolution rainfall can exhibit bias in magnitude and spatial variability to some extent as they are not a direct measurement of the spatial rainfall (Acharya et al., 2019a). In this regard, the uncertainty arising due to the spatial distribution could be quantified by adopting an ensemble approach. In this approach, we assume that generating an ensemble of rainfall scenarios by blending rainfall from multiple sources captures uncertainty in spatial rainfall. This allows us to estimate the uncertainty arising solely due to spatial variability of rainfall. This approach can be useful in capturing short-duration runoff events like flash floods and the intra-storm variability responsible for different runoff processes.

Overall, the aim of this study is to characterise hydrologicalmodel uncertainty involved in the high flow simulations using a simple rainfall-runoff model and ensemble rainfall input. Further, we explore the response of area of the basin and sub-basin on the uncertainty and how this uncertainty cascades from the upstream to downstream of a basin. We use the Global Precipiation Mission (GPM) rainfall product and rainfall radar data to create a rainfall ensembles in order to see the impact of ensemble input on high flows in the entire Macleay Basin and its three sub-basins of different sizes. We introduce the study area in Section 2; thereafter, the description of the ensemble generation and rainfall-runoff modelling is explained in Section 3. We present and discuss results, and summarise the conclusions in the subsequent sections.

2. THE STUDY SITE DESCRIPTION

The generation of ensemble requires GPM and radar rainfall, and therefore the selected study site should have radar rainfall coverage. Therefore we selected the Macleay basin which satisfies the above criteria and also had a few large events in past three years required for this study. The Macleay Basin, located in the New South Wales, extends from 30.00°S to 31.35°S and from 151.39°E to 152.41°E (Figure. 1). This basin is approximately 8,000 km^2 with larger areas of the northern tablelands, a sparsely populated region and the coastal area extending from foothills to coastal plains. The Macleay River Basin is bounded by the Great Dividing Range and the inland catchments of the Gwydir and Namoi Rivers in the west, while the coastal Hastings and Manning River catchments lie in the south and the coastal Clarence, Bellinger and Nambucca River catchments lie along the north sides. Further, the elevation of the catchment varies from 130 m in the lower reaches up to 1550 m in the northern and southern mountain ranges. The annual average precipitation is approximately 850 mm, which varies spatially within the catchment from 500 mm to 1100 mm. Monthly mean maximum temperature of the catchment goes up to 30°C during summer and 20°C in

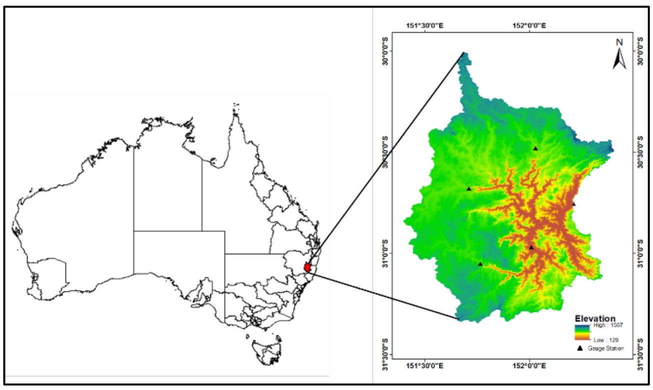

Figure 1. The Macleay catchment, study area

the winter, while monthly mean minimum temperatures in the summer and winter goes to 16°C and 6°C respectively. The Macleay River basin has a larger variability in its flow regime, and flooding may occur at any time of the year. Flooding in the Lower Macleay valley occurs every 2 – 3 years, and the largest floods have occurrence interval of 100 years (Ferguson et al. 1999).

3. METHODOLOGY

In this study, we use GPM precipitation data at 10km x 10km spatial resolution further downscaled to 2km x 2km spatial resolution for three years (2015-2017). Further, radar data along with the GPM precipitation is used to create 50 member rainfall ensembles at 2km x 2km spatial and hourly temporal resolution. A conceptual rainfall-runoff model, GR4H, coupled with Muskingum Routing (Overton, 1966) is used with observed precipitation and rainfall ensembles to generate streamflows at the basin outlet. The detailed description of GR4H model along with rainfall ensemble generation is given in further sub-sections.

3.1 Model Description

GR4H, an empirical rainfall-runoff hydrological model (Le Moine et al., 2008) is an hourly version of GR4J (Perrin et al., 2003) having two water storages, namely, production storage and routing storage. This model runs on an hourly time step and requires only two inputs, hourly rainfall (*P*) and hourly evapotranspiration (*ET*). It has only four parameters which are needed for optimisation during the calibration process. Firstly, the model distributes *P* by *ET* in order to estimate the effective rainfall (P_n) and net evapotranspiration (ET_n), given by:

If P > ET,

$$P_n = P\text{-}ET \text{ and } ET_n = 0 \tag{1}$$

If P< ET,

$$P_n = 0 \text{ and } ET_n = ET\text{-}P \tag{2}$$

The P_n is further redistributed among the storage (P_s) and surface runoff (P_n-P_s) (Figure 2). The P_s moves towards the production storage along with ET from the storage and percolation.

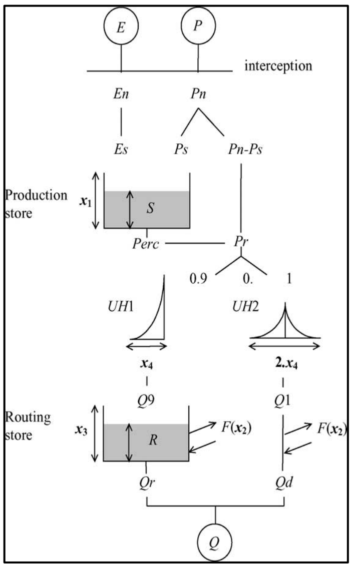

Figure 2. GR4H model description

Thereafter, 90% of the total surface runoff is routed by the unit hydrograph one (UH1) and the routing storage. The rest 10% of the total surface runoff is routed by unit hydrograph two (UH2). The net capacity of the production storage (X1) is one of the major calibrating parameter. Ground water exchange coefficient (X2) is the parameter which influences routing storage. Routing storage (X3), the amount of water stored in soil porous, and this value depends on type and humidity of soil. Time to peak (X4) ordinate of the hydrograph unit UH1 (hour) is the fourth calibrating parameter.

3.2 Ensembles Generation

In order to generate the required stochastic ensembles from radar estimates of precipitation, a simplified method is used by separating the radar rainfall image to signal and noise (Pegram et al., 2011; Seed et al., 2013; Nerini et al., 2017). Ensembles represent the spatial uncertainty of rainfall analysis such that it can work in the real-time (i.e. with 10 minutes). The descriptive flowchart for the ensemble rainfall (2km x 2km) generation from GPM precipitation (10 km x10 km) is shown in Figure 3. First, we considered rainfall analysis (R_a) and reference rainfall dataset (GPM in this study) (R_r) for bias correction based on empirical cumulative distribution function (ECDF) matching. Thereafter, the logarithmic transformation is applied to R_a and the respective exponential coefficient is determined (Niemi et al., 2016). Based on the power law of rainfall, the new spatial structure is defined. This spatial field is combimed with Gaussian white noise, convolved with power-law filter, to generate the ensemble members of perturbed rainfall. The generated ensembles are subjected to satisfy the reliability criteria. This reliability criteria is defined such that mean square error of ensemble mean is approximately equal to the ensemble variance (Renzullo et al., 2018).

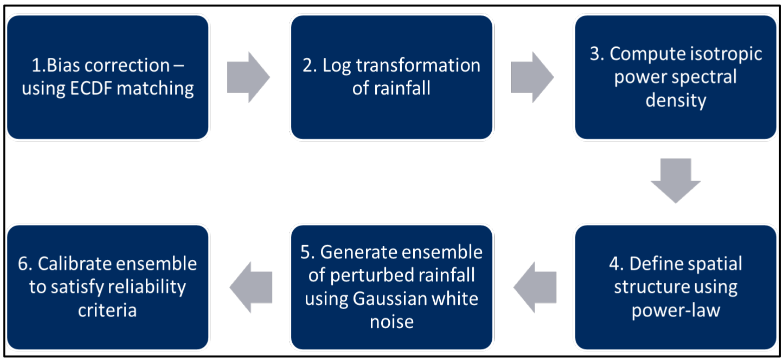

Figure 3. Ensemble generations for the GPM datasets

3.3 Simulations and different streamflow generations

The three sub-basins and the main basin where simulations are calibrated is shown in figure 4. The three sub-basins are namely, sub-basin id – 206025 (646 km^2), sub-basin id – 206014 (377 km^2), and sub-basin id – 206018 (860 km^2). The GR4H and Muskingum combined model is initially calibrated by using GPM data at sub-basins averaged at the outlet of Macleay Basin. Thereafter, the gridded rainfall is used as an input and the runoff is generated corresponding to the high streamflows. Further, in order to study the effect of rainfall uncertainties on the runoff generation, rainfall ensembles (50 in total at 2km x 2km spatial resolution and 1 hour as temporal resolution) are used as input to the model. The conceptual framework of the methodology followed in this study is given in the flow chart (Figure 5). Further, we compared and contrasted the runoff generated at the outlet by grid-wise simulations and basin averaged simulation with the observed streamflow at the outlet for peak flows (21/08/2016-31/08/2016 in this study). Thereafter, the ensembles are compared with the observed and GR4H simulated streamflow.

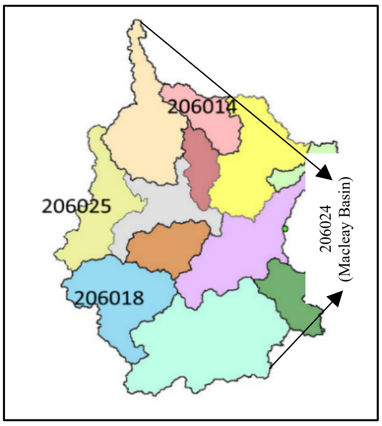

Figure 4. Sub-basins representation

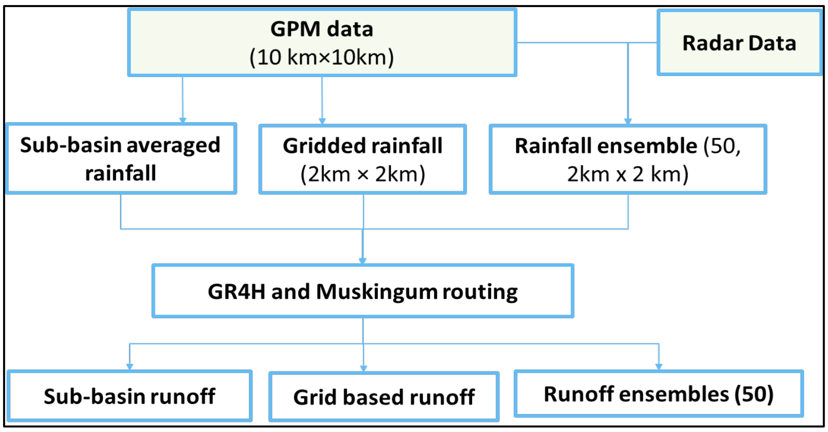

Figure 5. Conceptual framework for the methodology

4. RESULTS

4.1 Comparison of sub-basin wise and grid-wise streamflow with observed streamflow

A comparison of high flow for the entire basin, its sub-basins obtained from grid-based and sub-basin based simulation is shown in Figure 6. It is observed that grid-wise simulations over-predicted the streamflow in comparison to the observed streamflow for the Macleay basin and other two sub-basins (Basin 206014 and 206018) except one basin i.e. basin 206025. However, basin-wise simulations underestimate the runoff in all the sub-basins and Macleay basin. The maximum streamflow generated in the Macleay Basin during the shown study period is 600 cumec (grid simulations) while minimum streamflow is 300 cumec (basin-wise simulations). The other three sub-basins have streamflow ranging between 80 cumec (grid-wise simulation) to 30 cumec (basin-wise simulations). The lower values of runoff generation are obvious due to the smaller catchment size of the sub-basin. The grid-wise streamflow better simulated with observed streamflow as compared with sub-basin wise streamflow generations.

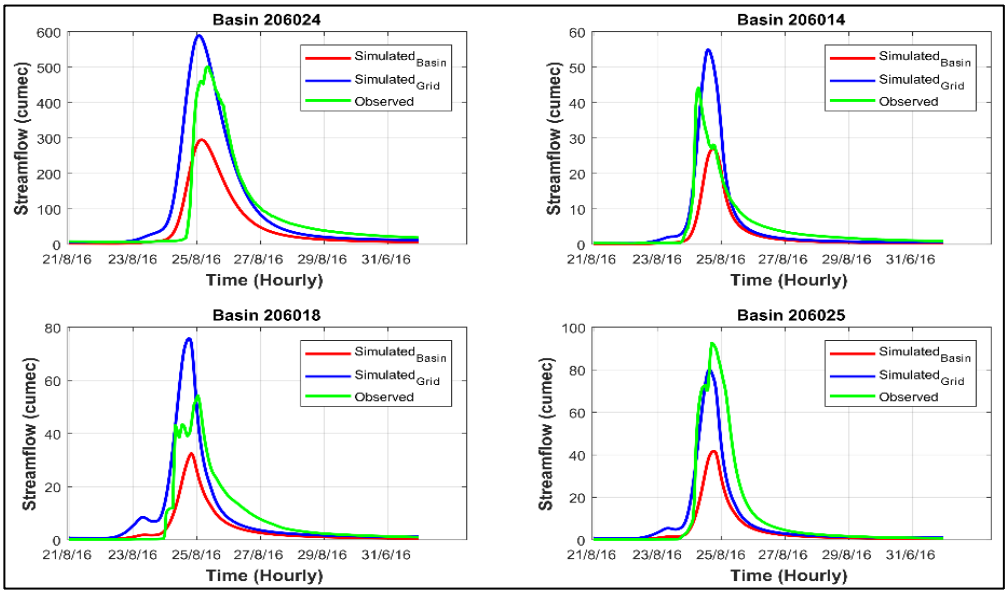

Figure 6. High flow comparison for observed streamflow with simulated streamflow at sub-basin and grid-wise

4.2 Ensemble streamflow generations and its analysis

The ensemble rainfall in the form of regular grid of size (2km x2 km) is used as input to the model. Based on the model configurations described in Section 4.1, the resulting runoff simulated for large events. Figure 7 shows observed and simulated streamflow for an event generated by rainfall ensembles (50 members) using grid based simulation, and deterministic rainfall field using grid-based and sub-basin based simulation at Macleay Basin and its three sub-basins. The peak of ensemble streamflow ranges between 400 cumec to 800 cumec in Macleay Basin where observed streamflow reached its maximum ~450 cumec. This shows that the ensemble streamflows captured the peak flows. Similarly, in the other three sub-basins also, the ensembles have captured the observed streamflow to a greater extent in comparison to deterministic sub-basin wise and grid-wise simulations.

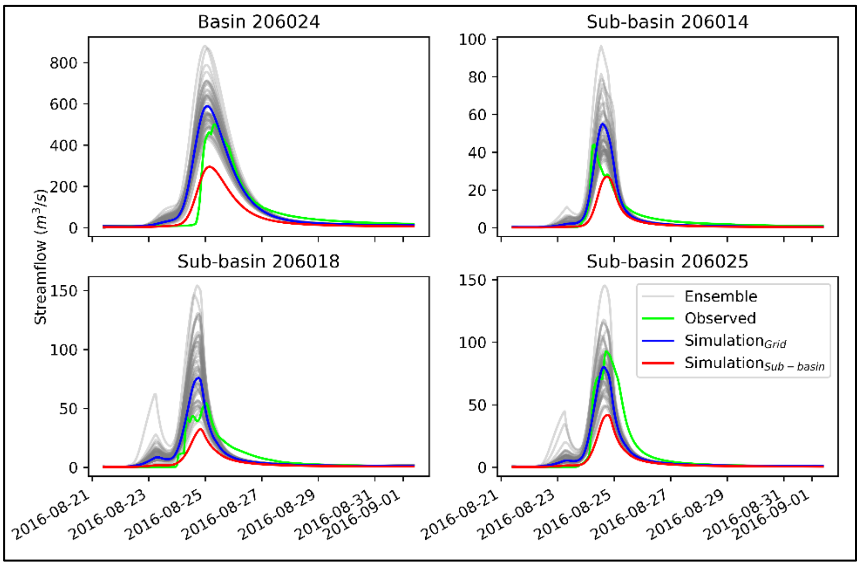

Figure 7. Ensembles comparison for high flow

Further, the ensemble streamflow also captures the grid-wise streamflow in all the basins. Although the ensemble streamflow could capture the pattern of observed streamflow, the peak runoff and time to reach the peak streamflow varies for Macleay basin and other three sub-basins. The boxplots for peak flow at each of the sub-basins and the Macleay Basin and time to reach this peak is shown in Figure 8.

The mean peak flow of ensemble (0.25 mm/hour) is approximately comparable to the observed peak flow (0.22 mm/hr) in Macleay Basin. However, the deviation increases between the ensemble mean peak flow and the observed peak flows at other three sub-basins. Further, it is observed that ensemble streamflow could not capture the time to peak in any of the sub-basin or Macleay Basin. It may be attributed to the difference in basin size.

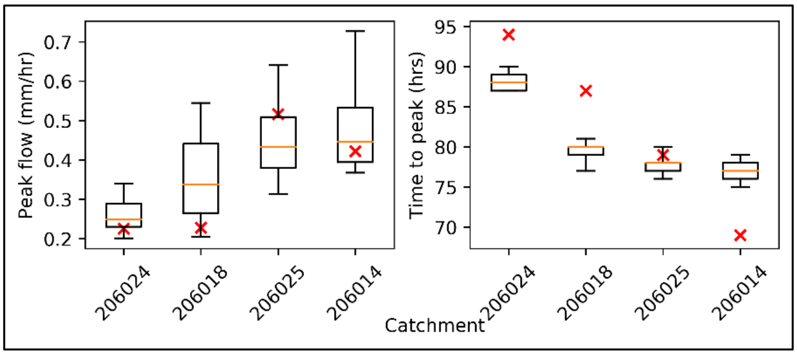

Figure 8. Peak flow and time to peak comparisons

5. DISCUSSION AND CONCLUSION

The grid-wise streamflow generation is comparatively better in capturing the peak flows in the Macleay Basin and sub-basin than the basin-wise streamflow output. It may be attributed to the fact that the gridded simulations used the same parameter throughout the simulations. As it is a conceptual hydrological model, the grid-based modelling results do better in capturing hydrological flows than basin averaged analysis (Srivastava et al., 2018; Paul et al., 2018; Tran et al., 2018). Further, this can also be contributed to smaller averaged streamflow at each sub-basins and more amount of overall losses at the basin scale. The ensemble streamflow have captured the observed streamflow comparatively better than the other simulated streamflow. Ensemble precipitation helps in generating a range of outputs which may better help to provide a nearly accurate range of high flows in the basin as shown in previous studies (Shrestha et al., 2015).

This study showed the role of input uncertainties in hydrological modelling and how the uncertainty in precipitation may be captured by using ensemble methods. The observed peak flow is seen to fall within the range of streamflow simulated using ensemble rainfall for all the basins. This means that the rainfall ensembles can be successfully applied to establish sub-daily operational streamflow forecast systems. The application of ensemble generation approach could also help reduce the uncertainty due to spatial dispalcement in rainfall field (Acharya et al., 2019a) and potentially improve the hydrological modelling. In addition to rainfall uncertainty, one can further incorporate other sources of uncertainty (parameter and initial condition) in hydrological modelling. The statistical analysis of the simulation results on the entire Macleay Basin and its sub-basins show significant differences in model performance at basin-wise, grid-wise, and ensemble rainfall as input.

ACKNOWLEDGEMENTS

The authors wish to thank the OzEWEX Summer Institute and its partners where this project was conducted, with special thanks to Albert van Dijk for organising and coordinating the program. Nikul Kumari is supported by the funding from the University of Newcastle Postgraduate Research Scholarship (UNRSC) 50:50.

REFERENCES

Acharya, S. C., Nathan, R., Wang, Q. J., Su, C. H., & Eizenberg, N. (2019a). An evaluation of daily precipitation from atmospheric reanalyses over Australia. Hydrology and Earth System Sciences Discussions, in review.

Acharya, S. C., Nathan, R., Wang, Q. J., Su, C. H., & Eizenberg, N. (2019b). An evaluation of daily precipitation from a regional atmospheric reanalysis over Australia. Hydrology and Earth System Sciences, 23(8), 3387-3403.

Beck, H. E., Vergopolan, N., Pan, M., Levizzani, V., Van Dijk, A. I., Weedon, G. P., Brocca, L., Pappenberger, F., Huffman, G. J. & Wood, E. F. (2017). Global-scale evaluation of 22 precipitation datasets using gauge observations and hydrological modeling. Hydrology and Earth System Sciences, 21(12), 6201-6217.

Bárdossy, A., & Das, T. (2008). Influence of rainfall observation network on model calibration and application. Hydrology and Earth System Sciences Discussions, 12(1), 77-89.

Beven, K., 2016. Facets of uncertainty: epistemic uncertainty, non-stationarity, likelihood, hypothesis testing, and communication. Hydrological Sciences Journal, 61 (9), 1652–1665.

Bárdossy, A., & Das, T. (2008). Influence of rainfall observation network on model calibration and application. Hydrology and Earth System Sciences Discussions, 12(1), 77-89.

Blöschl, G., & Sivapalan, M. (1995). Scale issues in hydrological modelling: a review. Hydrological processes, 9(3-4), 251-290.

Ferguson R., Lampert G. & Brierley G. (1999). River styles in the Macleay catchment, North Coast, NSW. Report to New South Wales Department of Land and Water Conservation. Department of Physical Geography, Macquarie University, Sydney.

Le Moine, N., Andréassian, V., & Mathevet, T. (2008). Confronting surface-and groundwater balances on the La Rochefoucauld-Touvre karstic system (Charente, France). Water Resources Research, 44(3).

Liu, Z. (2016). Comparison of integrated multisatellite retrievals for GPM (IMERG) and TRMM multisatellite precipitation analysis (TMPA) monthly precipitation products: initial results. Journal of Hydrometeorology, 17(3), 777-790.

Nerini, D., Besic, N., Sideris, I., Germann, U., & Foresti, L. (2017). A non-stationary stochastic ensemble generator for radar rainfall fields based on the short-space Fourier transform. Hydrology and Earth System Sciences, 21(6), 2777-2797.

Niemi, T. J., Guillaume, J. H., Kokkonen, T., Hoang, T. M., & Seed, A. W. (2016). Role of spatial anisotropy in design storm generation: Experiment and interpretation. Water Resources Research, 52(1), 69-89.

Overton, D. E. (1966). Muskingum flood routing of upland streamflow. Journal of Hydrology, 4, 185-200.

Pegram, G., Llort, X., & Sempere-Torres, D. (2011). Radar rainfall: separating signal and noise fields to generate meaningful ensembles. Atmospheric Research, 100(2-3), 226-236.

Paul, P. K., Kumari, N., Panigrahi, N., Mishra, A., & Singh, R. (2018). Implementation of cell-to-cell routing scheme in a large scale conceptual hydrological model. Environmental Modelling & Software, 101, 23-33.

Perrin, C., Michel, C., & Andréassian, V. (2003). Improvement of a parsimonious model for streamflow simulation. Journal of Hydrology, 279(1-4), 275-289.

Renard, B., Kavetski, D., Kuczera, G., Thyer, M., & Franks, S. W. (2010). Understanding predictive uncertainty in hydrologic modeling: The challenge of identifying input and structural errors. Water Resources Research, 46(5).

Renzullo, L.J., Velasco-Forero, C.A., Seed, A.W., Ebert, B.E., Majewski, L., Broomhall, M., Van Dijk, A. I. J. M., Rozas-Lorraondo, P., & Tian, S. (2018). Continental rainfall ensemble derived from multi-source blended analysis. BOM R&D Annual Workshop http://www.bom.gov.au/research/workshop/2018/workshop-program.shtml

Seed, A. W., Pierce, C. E., & Norman, K. (2013). Formulation and evaluation of a scale decomposition-based stochastic precipitation nowcast scheme. Water Resources Research, 49(10), 6624-6641.

Shrestha, D. L., Robertson, D. E., Bennett, J. C., & Wang, Q. J. (2015). Improving precipitation forecasts by generating ensembles through postprocessing. Monthly Weather Review, 143(9), 3642-3663.

Srivastava, A., Sahoo, B., Raghuwanshi, N. S., Singh, R. (2017). Evaluation of variable-infiltration capacity model and MODIS-terra satellite-derived grid-scale evapotranspiration estimates in a River Basin with Tropical Monsoon-Type climatology. Journal of Irrigation and Drainage Engineering, 143(8), 04017028.

Srivastava, A., Sahoo, B., Raghuwanshi, N. S., Chatterjee, C. (2018). Modelling the dynamics of evapotranspiration using the Variable Infiltration Capacity model and regionally calibrated Hargreaves approach. Irrigation Science, 36(4-5): 289-300.

Tran, Q. Q., De Niel, J., & Willems, P. (2018). Spatially distributed conceptual hydrological model building: a generic top-down approach starting from lumped models. Water Resources Research, 54(10), 8064-8085.

van Dijk, A. I. J. M., & Renzullo, L. J. (2010). Water resource monitoring systems and the role of satellite observations. Hydrology and Earth System Sciences, 15, 39–55.