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Challenges in Deriving Representative Rainfall-Runoff Model Parameters for Flood Forecasting: Insights from Sixth Creek, South Australia

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Abstract: Design flood estimation in data-sparse catchments presents significant challenges because limited streamflow records restrict the application of Flood Frequency Analysis (FFA). In such situations, rainfall–runoff modelling is often required; however, deriving representative catchment-specific model parameters is difficult due to high variability introduced by the single-event calibration processes. This study evaluated four pooling approaches to derive representative parameter sets for HEC-HMS model validation in flood forecasting, using the Sixth Creek catchment in South Australia as a case study. Two weighting methods and two simpler strategies (mean and median) were tested. While individual event calibrations performed well (NSE 0.70–0.90), all pooled parameter sets showed poor validation performance, with most NSE values negative. These findings highlight the limitations of single-event calibration and emphasise the need for advanced multi-event calibration techniques combined with multi-objective optimisation algorithms to improve rainfall–runoff modelling in data-sparse catchments.

Keywords: *HEC-HMS, event-based modelling, representative parameter estimation, catchment hydrology*

1. INTRODUCTION

Accurate design-flow estimation and real-time flood forecasting are critical for flood management, infrastructure planning, and hydraulic design. While Flood Frequency Analysis is preferred when long-term, high quality streamflow records exist, many catchments lack such data, making rainfall–runoff modelling essential. Among widely used models in Australia, HEC-HMS is notable for its broad application and ability to simulate complete catchment processes. However, a key challenge is selecting representative parameters, as single-event calibration often yields variable estimates due to differences in rainfall, antecedent soil moisture, and baseflow conditions.

To address this issue, Kemp and Alankarage (2023) proposed a weighting method to combine single-event calibrated parameters into a single representative set, which was successfully applied to the Inverbrackie Creek catchment in the Mount Lofty Ranges, South Australia. This study extends their work by testing the validity of that method in the Sixth Creek catchment at Castambul, South Australia, which exhibits similar climatic conditions. The performance of this method was compared against the approach proposed by Wang et al. (2021), as well as two simpler pooling strategies, the arithmetic mean and the median. A HEC-HMS model was calibrated using six selected rainfall events, and model validation on six other independent events was used to assess the effectiveness of the four pooling methods.

2. METHODS

This study applied an event-based HEC-HMS model to the Sixth Creek catchment, located in the western Mount Lofty Ranges, South Australia. The catchment, which forms part of the Torrens River system, covers an area of approximately 44.2 km² and is predominantly forested. Twelve flood events producing the highest peak flows between 1983 and 2025 were identified from streamflow records, where six were used for calibration and six were reserved for validation. Both rainfall and streamflow data were used at a 15-minute temporal resolution to ensure accurate representation of event dynamics.

The HEC-HMS framework was configured using the Initial Loss-Continuous Loss (IL–CL) method to represent rainfall losses, the Clark unit hydrograph for rainfall–runoff transformation, and a recession approach to simulate baseflow, consistent with the methodology of Kemp and Alankarage (2023). Representative parameter values were derived using two different weighting approaches. The first approach proposed by Kemp and Alankarage (2023), in which the Weighting Factor 1 (WF_1) is defined as the ratio of observed peak flow to the Root Mean Square Error (RMSE) of the simulated flow during calibration (Equation 1). In this equation, Q_{op} represents the observed peak flow, q_o and q_c denote the observed and simulated discharges, respectively, and n is the number of time steps in the event hydrograph. The individual WF_1 values were then normalized by dividing each by total sum of WF_1 values across the events.

$$WF_1 = \frac{Observed\ peak\ flow}{Root\ mean\ square\ error} = \frac{Q_{op}}{\sqrt{\frac{\sum_1^n (q_o - q_c)^2}{n}}} \qquad (1)$$

The second approach, proposed by Wang et al. (2021), implemented Weighting Factor 2 (WF_2) which combines the Pearson correlation coefficient (r) and the root mean square error (RMSE) for each event, as shown in Equation 2, where *n* is the total number of events.

$$WF_2 = \frac{r + \frac{1}{RMSE}}{w_k}, \text{ where } w_k = \sum_1^n \left(r_i + \frac{1}{RMSE_i}\right) \qquad (2)$$

The model validation performance was evaluated using Nash–Sutcliffe Efficiency (NSE), coefficient of determination (R^2), and Percent Bias (PBIAS). Four methods for deriving representative parameters from the event-calibrated sets were compared: weighting factors (WF_1 and WF_2), the arithmetic mean, and the median of the calibrated parameter values.

3. RESULTS

Model calibration achieved good performance, with NSE values ranging from 0.70 to 0.90 and generally low PBIAS. However, parameter estimates varied considerably between events, highlighting the challenge of deriving a representative set of parameters. When parameters were pooled using WF_1, four of the six validation events resulted in negative NSE values, while the remaining two events achieved NSE values below 0.5. Application of WF_2 showed marginal improvement, with three events yielding positive NSE values; however, these values remained below 0.5 and only slightly better than those resulted from the WF_1 approach. Overall, using WF_2 did not lead to a substantial enhancement in model performance.

Simpler pooling methods based on the arithmetic mean and the median of the calibrated parameter sets produced mixed results. These approaches showed performance trends similar to that of WF_2. Notably, the same three events consistently performed better under all three of these methods. Among them, the median-based parameter set yielded slightly better overall performance than both the mean-based and WF_2 approaches. However, none of the parameter pooling methods produced satisfactory results during model validation. One validation event consistently demonstrated markedly poor performance across all methods, producing considerably high negative NSE values. Closer examination revealed that this event featured multiple flow peaks, which the model was unable to capture effectively. Such multi-peaked behaviour was not present in the calibration events, suggesting that the model may be less reliable when applied to events with more complex hydrograph patterns.

4. CONCLUSION

The results underscore the inherent challenge of deriving representative parameters from single-event calibrations due to significant variability in parameter estimates. Although the WF_1 approach showed promising outcomes in a nearby Mount Lofty Ranges catchment, it did not produce satisfactory validation results for the Sixth Creek catchment. The WF_2 offered only marginal improvement, with limited predictive skill. These findings reinforce that each catchment responds differently, and heterogeneity in physical and hydrological characteristics strongly influences parameter transferability. Broader testing across multiple catchments is required to assess the wider applicability of different parameter pooling approaches for design flood estimation. At the same time, more advanced techniques such as joint event calibration combined with single or multi-objective optimisation algorithms may offer improved pathways for deriving robust representative parameter sets to improve rainfall-runoff modelling.

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