https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Uncovering a Key Predictors for Enhancing Daily Streamflow Simulation Using Machine Learning

Arash Aghakhani[a,b,*], David E. Robertson[a], Valentijn R.N. Pauwels[b]

[a] Commonwealth Scientific and Industrial Research Organisation (CSIRO), Clayton 3168, Australia

[b] Department of Civil Engineering, Monash University, Clayton, VIC 3800, Australia

Correspondence: Arash Aghakhani, arash.aghakhani86@gmail.com

Abstract

The sequence of droughts and wetter periods in Australia poses challenges for long-term hydrologic modelling. This paper develops a novel machine learning-based approach to uncover key predictors that improve daily streamflow predictions during and after the Millennium drought (1997 to 2009) in 39 gauged sub-catchments in Western Victoria, Australia.

For this purpose, a hybrid approach is adopted, combining simulations from the GR4J hydrological model with physical data as forcing (predictors) for multiple ML algorithms to identify the key predictors for improving streamflow prediction. GR4J is a widely used operational hydrological model in Australia. ML models including predictors representing long-term runoff coefficient and short-term runoff and rainfall showed the greatest improvement in streamflow predictions, particularly for low flows. This suggests that GR4J has limited ability to capture short/long-term persistence and therefore model enhancement should focus on these shortcomings. All ML algorithms resulted in improved streamflow prediction, with Multilayer Perceptron (MLP) consistently yielding the highest Nash Sutcliffe Efficiency, and Random Forest showing the strongest improvement in terms of low-flow prediction. Long-term runoff coefficient and machine learning were most effective in catchments with lower long-term runoff coefficients. Overall, this study provides insights for water resources management in drought-prone regions, highlighting the key predictors in the combination of ML and hydrological modelling to improve streamflow predictions during and after droughts.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Keywords: Machine learning, streamflow prediction, Millennium drought, Climate change, Hydrological model, long/short-term runoff coefficient

1 Introduction

Climate change is projected to increase the frequency and severity of droughts in many parts of the world due to reductions in rainfall (Fowler et al., 2022). Analysis of historical multi-year droughts can therefore provide insights and understanding of hydrological responses likely to be observed under future climate changes (Fowler et al., 2022). Australia's Millennium drought (1997 to 2009) serves as a noteworthy example(Van Dijk et al., 2013). During the Millenium drought, a substantial portion of the southern part of Australia faced an extended period of dry conditions. The impact was particularly severe in densely populated areas of Southeastern and Southwestern Australia (Bureau of Meteorology, 2024) (Wallis et al., 2011)(Southwest Victoria alliance-Advocacy Priorities 2021/22, 2024)(Primary Production Landscapes of Victoria - Northwest Victoria, (2024)).During the Millennium drought, soil drying and declining water tables harmed flora and fauna, leading to more wildfires and dust storms (Heberger, 2012). The sheep population during the Millennium drought in Australia declined by half (Heberger, 2012). Water shortages due to the Millennium drought led to decreased water allocations for irrigation, imposed water restrictions in urban areas, and prompted considerable investments in infrastructure, such as the construction of desalination plants and pipeline installation (Van Dijk et al., 2013).

Southwestern Victoria, as part of southeastern Australia severely impacted during the Millennium Drought, reflects the nation's broader struggle with prolonged dry conditions. During the Millenium drought, alterations, or shifts (Saft et al., 2015), in rainfall–runoff relationships were observed in numerous Victorian catchments but were absent in others (Fowler et al., 2022). These shifts in rainfall-runoff relationships are a form of hydrologic non-stationary. Non-stationarity in hydrology refers to the phenomenon where the statistical properties of hydrological processes, such as rainfall patterns and runoff relationships, change over time. In other words, the influence of forcing variables in one period will differ from those experienced in a separate period (Slater et al., 2021). During the Millennium

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

drought reductions in streamflow were larger than initially anticipated based on the observed rainfall reductions (van Rensch et al., 2023). The physical mechanisms behind these shifts are not well understood (Fowler et al., 2022). According to Peterson et al. (2021), the transitions towards reduced streamflow can exhibit remarkable persistence, as certain watersheds appear to maintain a changed state even after returning to nearly average climate conditions. In these persisting cases, a year of typical rainfall now results in lower streamflow compared to pre-drought levels.

Streamflow prediction is challenging due to its high complexity, non-stationarity, and non-linearity of hydrological processes (Yaseen et al., 2015). Many Process-Based (PB) hydrological models have been developed for streamflow prediction. However, due to the uncertainties in the formulation and parameterisation of the physical processes, and also the errors in the forcings and validation data, these models exhibit limited capability in capturing the non-stationary in hydrological datasets (Cheng et al., 2020). Conceptual hydrological models are widely used for climate change impact analyses due to their higher computational efficiency, facilitating rapid assessments across multiple catchments and for long-term simulations (Zheng et al., 2024) However, their simplified representation of the physical processes potentially overlooks the ways within-catchment hydrological processes could intensify or alleviate changes in runoff generation under a changing climate (Robertson et al., 2023). Since the physical mechanisms behind the shifts in rainfall-runoff relationships are not well understood, such shifts in response to extended drought are challenging to predict. Furthermore, it is widely accepted that the use of hydrological models for prediction in changing conditions remains a significant concern in hydrology (Blöschl et al., 2019).

Model validation against a diverse range of conditions is a crucial step in building robust models (Fowler et al., 2022). Hydrological models developed and calibrated based on pre-drought data are not capable of properly predicting the streamflow during the drought (Chiew et al., 2014). Fowler et al. (2021) studied the performance of the GR4J hydrological model in Victoria's catchments for the Millennium drought and suggested that limitations in conceptual hydrological models capabilities to project runoff under a drying climate might be due to implicit upper limits on the soil moisture deficit. Chiew et al. (2014) modelled 20 catchments in South-Eastern Australia, using the SIMHYD model, and

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

found that pre-drought optimised parameter values resulted in very poor Millennium drought daily streamflow simulations. They stated that this poor performance is related to the hydrologic non-stationarity.

Machine learning models have proven highly effective in modelling natural systems because they do not make prior assumptions on the form of equations describing physical processes that are necessary in traditional models (Reis et al., 2021). Over the past two decades, there has been substantial advancement in the application of artificial intelligence and machine learning (ML) methods to predict non-linear hydrological responses (Pradhan et al., 2020), and generate valuable insights into the physical mechanisms behind hydrologic non-stationarities (Hao and Bai, 2023). The popularity of ML models for streamflow prediction is related to their relative ease of application, competitive computational performance and prediction accuracy (Pham et al., 2021). Machine learning methods are also less rigid in assumptions used to characterize the probability distribution of model errors than other methods, including statistical modelling. PB and ML approaches can complement each other with respect to their strengths and limitations. Hydrologic processes that preserve the mass and energy balance can be captured by a PB model, while other processes not incorporated in a PB model can be covered by the data-driven ML algorithm. Thus, an effective strategy is a hybrid combination of both approaches to improve hydrologic simulation (Konapala et al., 2020).

In ML, computers learn from data patterns to make predictions without the need for code development by the user. Input data (predictors) are used to predict output variables. Various machine learning methodologies have been employed in hydrological research for predicting streamflow, (Deo and Şahin, 2016; Petty and Dhingra, 2018; Yaseen et al., 2016). These approaches are based on diverse techniques such as Linear Regression, Multiple Linear Regression (MLR), Ridge regression, Gradient Boosting and its variants, neural networks (NN), specifically Multilayer Perceptron (MLP), and long short-term memory (LSTM), support vector machines (SVM), Decision tree, and Random Forest (RF), among others. Recent research indicates that ML models exhibit robustness and efficiency, often surpassing the performance of traditional hydrological models, including both conceptual and physically-based approaches, (Akusok et al., 2015; Rozos et al., 2022; Worland et al., 2018).

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Numerous reviews of the use of artificial intelligence and machine learning for hydrological applications have been published (Ng et al., 2023; Mohammadi, 2021; Yaseen et al., 2015). These reviews have all concluded that ML methods are highly suited to runoff prediction and forecasting applications due to their ability to represent non-linear and highly complex relationships between prediction variables and their predictors, and integrate a large range of complex and noisy datasets published (Ng et al., 2023; Mohammadi, 2021; Yaseen et al., 2015)

However, no standardised guidance exists for selecting ML methods to achieve optimal simulation accuracy (Hao and Bai, 2023) and choosing a single ML algorithm with high predictive accuracy is challenging, because algorithm performance depends on the specific datasets used and problem being addressed (Hao and Bai, 2023; Worland et al., 2018). A number of studies have reported varying outcomes regarding the comparison of the performance of different algorithms (Section 2.2.2.8). The algorithm is not the only factor of influence on the prediction results, the quality and quantity of the input data (predictors) has been shown to have a strong impact as well.

Moosavi et al. (2022) highlighted that the volume of input data (predictors) had stronger impact on the prediction accuracy in comparison to the model type. The lack of adequate predictor selection, or the use of an excessive number of predictors, affects the precision and stability of prediction models. This situation also necessitates a substantial amount of memory and computational resources for training and validation procedures (Reis et al., 2021). Therefore, identifying a suitable set of predictors is a crucial step in the ML modelling process. ML algorithms may produce less accurate and less interpretable results when working with insufficient data, or with data containing irrelevant or redundant information. In hydrologic problems, nonlinear approaches are often preferred for determining the type of model inputs, given the demonstrated highly non-linear nature of the input–output relationships (Lima et al., 2016).

Published studies have primarily focused on enhancing streamflow forecasting at the sub-catchment scale through machine learning, rather than finding the predictors that lead to the greatest improvement in the performance of predictions across a range of catchments. Additionally, there is a literature gap on how machine learning can be used to improve hydrological models and to identify potential

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

enhancements that could be globally applicable. Therefore, in this study, ML is employed using a combination of hydrological model outputs and physical data as predictors to investigate possible improvements in prediction performance and identify components missing in the hydrological model conceptualisation. For this purpose, GR4J, a simple yet efficient hydrological model (Arsenault et al., 2019), appropriate for a range of climate conditions and commonly used in Australia (Stephens et al., 2019) is used in this study.

The objectives of this study are: (1) to explore the effectiveness of using a combination of GR4J and physical data as predictors for machine learning algorithms for streamflow prediction in Western Victoria, Australia, during the drought and the post-drought periods, based on pre-drought calibration, and (2) to reveal the catchment data that are overlooked or are too uncertain for the employed hydrological model structure or configuration. This can be achieved by identifying the predictors with a significant impact on the improvement of the model results, incorporating them as essential physical parameters in the conceptual hydrological model, or by making alterations to the structure of the hydrological model.

The paper is structured as follows: Section 2 describes the case study area and the methodology used in this study. Section 3 presents results and discussion of the performance of hydrological model and proposed ML models, followed by section 4 that summarises the key findings and conclusions from the paper.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

2 Materials and methods

2.1 Case study

For this case study we use streamflow data for 39 gauged sub-catchments of 9 major catchments in western Victoria, Australia. This region depends significantly on agriculture, with approximately 81% of the land use having been developed for agricultural uses (Wallis et al., 2011), and plays a vital role in Australia's agricultural and forestry sectors. It contributes significantly to the nation's dairy production generating 2.3 billion Australian dollars, or 27% of the total national value, annually. In addition, it covers 17% of Australia's forest plantations (Southwest Victoria alliance-Advocacy Priorities 2021/22, 2024). Northwestern Victoria contains 40% of Victoria's dryland agriculture focusing mainly used for cereal cropping. Another significant land use in this area is grazing and production from native vegetation, accounting for 13% of Victoria land area (Primary Production Landscapes of Victoria - Northwest Victoria, 2024). This region has been chosen due to the notable influence of the Millennium drought on the streamflow and its importance on Victoria's economy.

Figure 1 shows an overview of the study area. The study sub-catchment range in size from 4.5 km² to approximately 2,677 km². The majority of the river runoff occurs during the austral winter and spring, primarily attributed to rainfall. The details of the sub-catchments and stream gauge stations can be found in Appendix (Table A. 1 and Figure A. 1). Streamflow data were extracted from the Bureau of Meteorology (BoM) Hydrologic Reference Stations (Hydrologic Reference Stations, 2024). Streamflow data are quality controlled using the quality flags provided, removing observations characterised as estimates, poor or unknown quality (Zhang et al., 2016). Catchment average forcing data, specifical are derived by taking area-weighted averages of the Australian Gridded Climate Data (Jones et al., 2009), rainfall and AWRA potential evapotranspiration (Frost, 2018).

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

2.2 Methods

To quantify the impact of the Millennium drought, changes in the mean daily rainfall and mean daily streamflow were calculated using the following equations:

$$Rainfall\ change = \frac{rainfall_{P2} - rainfall_{P1}}{rainfall_{P1}} \times 100 \quad \textit{Eq. 1}$$

$$Streamflow\ change = \frac{Streamflow_{P2} - Streamflow_{P1}}{Streamflow_{P1}} \times 100 \quad \textit{Eq. 2}$$

Where:

$Rainfall_{P1}$: mean daily rainfall in the period from 1988-01-01 to 1996-12-31 (pre-drought)

$Rainfall_{P2}$: mean daily rainfall in the period from 1997-01-01 to 2018-12-31 (drought and post-drought)

$Streamflow_{P1}$: mean daily Streamflow in the period from 1988-01-01 to 1996-12-31 (pre-drought)

$Streamflow_{P2}$: mean daily Streamflow in the period from 1997-01-01 to 2018-12-31 (drought and post-drought)

Since this study investigates the integration of results from a conceptual hydrological model with ML algorithms, the remainder of this section focuses on a general discussion on both the conceptual hydrological model and ML algorithms. Subsequently, the explanation of the proposed models is provided for comprehensive understanding of the combined approach used in this research.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

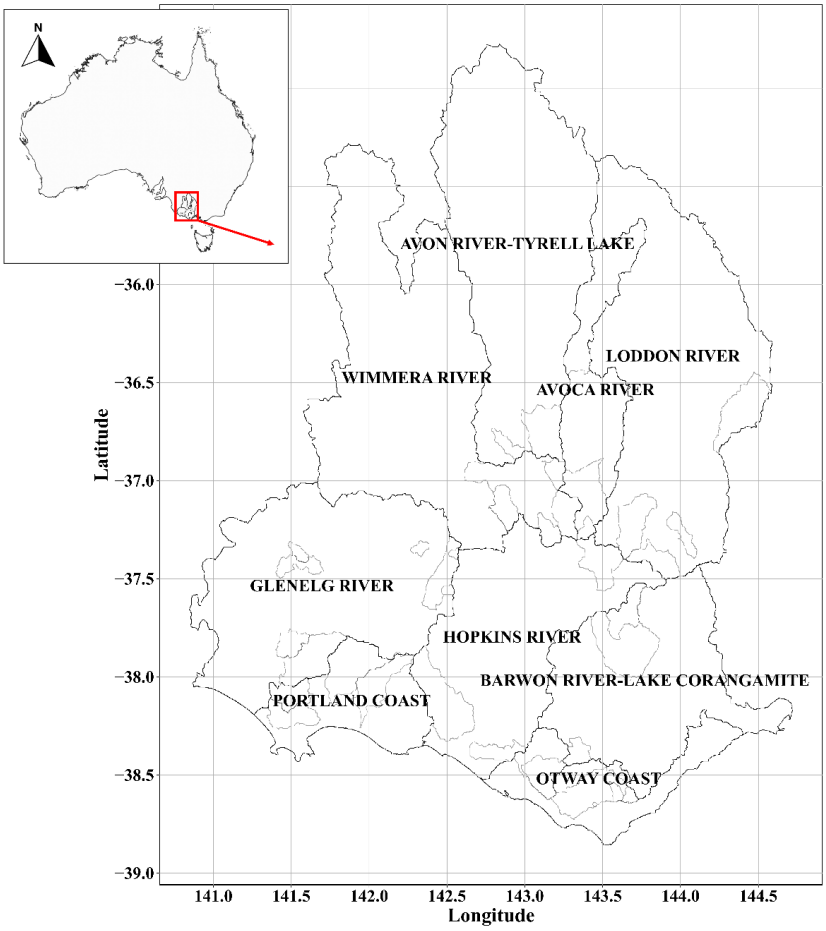


Figure 1. Overview of the catchments and sub-catchments used in this study (projection: EPSG:4326).

2.2.1 Hydrological models

The hydrological model used as a predictor for the ML models in this study is GR4J (Perrin et al., 2003). A schematic of GR4J is shown in Figure 2. This model is a four-parameter model that has been demonstrated to perform well in Australia. Model calibration and simulation was undertaken using the SWIFT2 (Short-term Water Information and Forecasting Tools) software (Perraud et al., 2015). The GR4J model parameters {X1, X2, X3 and X4} were calibrated by maximising the Nash-Sutcliffe Efficiency (NSE) using the Shuffled Complex Evolution (Aryal et al., 2020; Duan et al., 1994; Perrin et al., 2003).

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

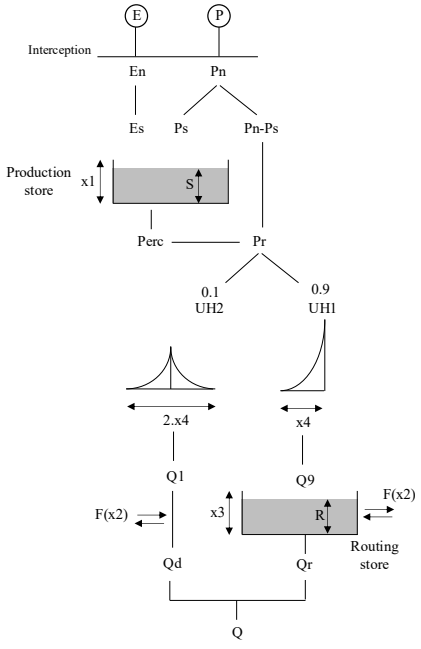


Figure 2 Diagram of GR4J hydrological model, with parameters derived from (Perrin et al., 2003)

2.2.2 Machine learning algorithms

Various machine learning algorithms are assessed in this study, namely Linear Regression, Ridge Regression, Support Vector Regression (SVR), Decision Tree, Random Forest, Gradient Boosting, and MLP. While all algorithms improved streamflow prediction accuracy, only the results of Random Forest, Gradient Boosting, and MLP are presented as they produced the best performing predictions (Ayzel et al., 2021; Lees et al., 2021; Rozos et al., 2022).

2.2.2.1 Random Forest regression

Random Forest regression generates predictions from an ensemble of regression relationships fitted over subsets of the predictor space that are defined using decision trees. This algorithm enhances the stability of decision trees by randomly sampling from the training data with replacement and aggregating the results. The combination of diverse trees also reduces prediction errors. This ensemble method is referred to as Random Forest, given that numerous trees are grown in a 'random' manner (Li et al., 2020). Random Forest is a simple and fast algorithm and one of the most powerful statistical

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

learning methods. It has the ability to work with very large datasets and is widely used in hydrological applications (Roy and Larocque, 2012; Szczepanek, 2022). Random Forest avoids assuming a global functional relationship and uses a local fitting approach through recursive partitioning. It exhibits flexibility regarding the distributional assumptions of model residuals (Li et al., 2020). This algorithm decreases variance by averaging decisions across diverse classifiers. Additionally, it diminishes bias when individual classifiers are adequately complex for the given subset of features (Yeturu, 2020). Random forest is considered in this study since many previous comparisons stated its remarkable performance (Bentéjac et al., 2021) and its key advantage in avoiding overfitting issues through an ensemble of permutations. Additionally, RF model evaluates the importance of predictor variables, enhancing interpretability compared to methods like artificial neural networks (ANNs) and SVR (Tongal and Booij, 2018)

2.2.2.2 Gradient Boosting

Gradient boosting algorithm is widely recognised as one of the most powerful algorithms (Wang et al., 2022) which can fit complex nonlinear relationships (He et al., 2020). Gradient boosting iteratively combines weak learners, which are slightly better than random, to form a suitable learner. This technique is commonly used for regression tasks. The objective of gradient boosting, when applied to a training dataset, is to minimise the expected value of a specified loss function to approximate the data (Bentéjac et al., 2021). Gradient boosting algorithms are well-known for their ability to effectively handle missing data and intricate relationships (Kumar et al., 2023). This method is commonly employed with decision trees of a fixed size as the base learners. Boosted decision trees are widely recognised as among the most effective prediction algorithms available today (Biau et al., 2019). In this study, gradient boosting is applied as a method for addressing a regression problem.

2.2.2.3 MLP

Multilayer Perceptron (MLP) is the most popular type of neural network in hydrology, renowned for its excellent performance in predicting streamflow (Boucher et al., 2020; Mohammadi et al., 2020; Rahimzad et al., 2021). This algorithm is a feedforward artificial neural network, which consists of interconnected nodes organised into three types of layers: input, hidden, and output. The input layer

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

transmits input values to the hidden layer without performing any operations on the input signal. The hidden layer processes signals from the input layer nodes, transforming them into signals distributed to all output nodes. The output nodes, in turn, further transform these signals into final outputs. This architecture is particularly effective for addressing non-linear problems (Onyari and Ilunga, 2013). In this study the MLP had 1 hidden layer and 100 neurons.

2.2.3 Model application

An overall schematic of the applied methodology is provided in Figure 3. Data were divided into training and test periods that extended from January 1, 1988, through December 31, 1996, representing the pre-drought period. Independent predictions were performed for the period January 1, 1997, through December 31, 2018, covering the Millennium drought and post-drought periods. Calibration and optimisation were conducted for the training and test periods only, and the subsequent simulation was carried out for the prediction period.

In the implementation of the machine learning analysis, different combinations of various predictors were considered in addition to the outcomes of the hydrological model. These predictors include rainfall, potential evapotranspiration, short-term streamflow memory, short-term rainfall memory, and long-term runoff coefficient. Short-term streamflow memory is characterised by the average streamflow over the preceding two days. Similarly, short-term rainfall memory is characterised by the average rainfall over the previous two days, offering a snapshot of recent precipitation patterns. The short-term rainfall and streamflow are expected to provide insight into the hydrological responses lag. The long-term runoff coefficient was derived by evaluating the ratio of cumulative runoff to cumulative rainfall for a five-year window leading up to each date. The long-term runoff coefficient is assumed to be associated with changes in catchment characteristics and particularly those related to surface–groundwater interactions (Robertson et al., 2023).

Eight ML models were assessed through different combinations of predictors, as outlined in Figure 3. For models 5 and model 6, an intentional effort was undertaken to account for the influence of long-term runoff coefficient on the estimation of the fraction of the rainfall contributing to streamflow. This

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

is achieved by multiplying the derived ratio of the five-year streamflow to precipitation, with both the rainfall and short-term rainfall memory components.

For each model, all ML algorithms listed in section 2.2.2 were trained using the SKlearn package in python, using data for the period January 1, 1988, through December 31, 1996. The objective function of all algorithms is squared error. The ML training process requires specification of training and testing subsets. The division of the data into training and testing periods can have a material impact on the fitted algorithm and its predictive performance. For this study, we adopted an 80:20 ratio of training to testing periods. The ML model training process was repeated ten times, each time randomly allocating data for the period January 1, 1988, through December 31, 1996 to the training and testing periods. All ten of the fitted ML models were retained to form an ensemble.

The fitted ML models were then used to generate predictions for the period January 1, 1997, through December 31, 2018. When the ML models are in predictive mode, the predictors representing long-term and short-term streamflow memories can be derived from observations. Using streamflow observations, the ML model's predictions are continually adjusted by the most recent observation, and predictions are equivalent to lead-one forecasts forced by perfect rainfall forecasts. The process begins by initialising the model with historical data. Then, the model predicts streamflow for the first day using the most recent observations. After each prediction, the observed streamflow for that day is integrated into the model as input for the following day prediction. This iterative process continues for the prediction of the following days. This evaluation will inform limitations in the structure of the GR4J model and identify processes, such as short-term or long-term memory, that may require improvement. Additionally, if potential evapotranspiration has a significant impact, it suggests that either the related formulation in the GR4J model or the observations may require further investigation.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

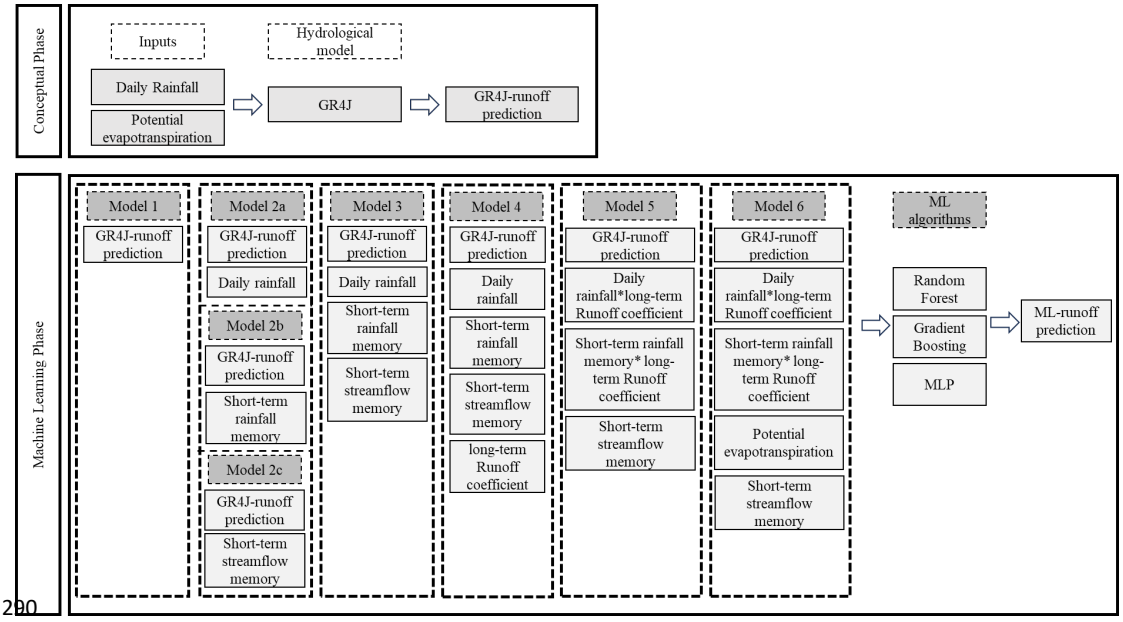


Figure 3 Schematic of the applied methodology.

The performance of the GR4J and ML models was assessed using the Nash-Sutcliffe Efficiency (NSE) and NSE of log-transformed flows. To assess the model performance for low-flows, the NSE of log-transformed flow was investigated, because logarithmic transformation increases the sensitivity of model performance assessment to low flow values (Romanowicz, 2007). To provide insight into the performance across the range of catchments investigated, exceedance curves for performance measures were generated. Where an ensemble of ML models is established, an ensemble of predictions is generated, one for each model, the NSE computed separately for each ensemble member and then averaged to produces a mean NSE value across the prediction ensemble.

The classification system for NSE of daily flow simulations devised by (Moriasi et al., 2015) was used to categorise model performance Table 1.

Table 1. Model performance evaluation criteria for daily flow, based on the NSE value.

Very good	Good	Satisfactory	Not Satisfactory
NSE > 0.80	0.70 < NSE ≤ 0.80	0.50 < NSE ≤ 0.70	NSE ≤ 0.50

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Sensitivity analyses were conducted to evaluate the impact of varying two parameters: the number of days considered for short-term pre-streamflow in model 2c and the duration of years used to calculate the long-term runoff coefficient in model 5. Specifically, the analysis examined short-term periods ranging from 2 to 7 days while keeping the long-term period fixed at 5 years, and separately, long-term periods spanning 1 to 5 years with a fixed short-term period of 2 days, to assess how these variables affect model performance and prediction accuracy.

3 Results and discussion

The focus of this study is to understand the additional information required to improve streamflow simulations in a period with different rainfall-runoff characteristics for fitting models. Therefore, we firstly assess the differences in mean daily rainfall and runoff between the model training and prediction periods (Figure 4). The decrease in the streamflow across all sub-catchments in this region is considerably larger than the reduction in the precipitation. This observation highlights the significance of this region as a proper case study, prompting further investigation to understand the underlying reasons for this discrepancy.

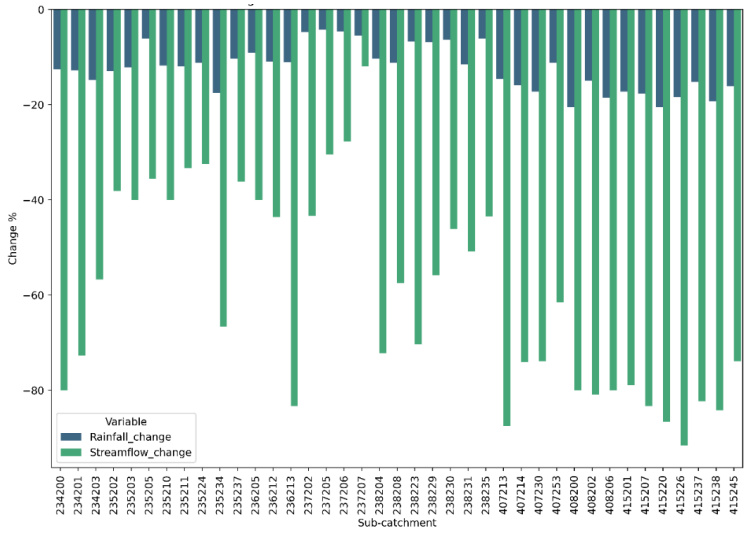


Figure 4. Comparison of the mean daily rainfall and streamflow change from 1988-01-01 to 1996-12-31 (pre-drought) and from 1997-01-01 to 2018-12-31 (drought and post-drought).

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

The NSE values of the GR4J hydrological model predictions during the drought and post-drought prediction periods are shown in Figure 5. The NSE for the prediction period are considerably lower than the calibration period for all catchments. For the prediction period, the performance of the GR4J hydrological model simulations can be classified as "satisfactory" for only 5 sub-catchments, with the remainder "not satisfactory".

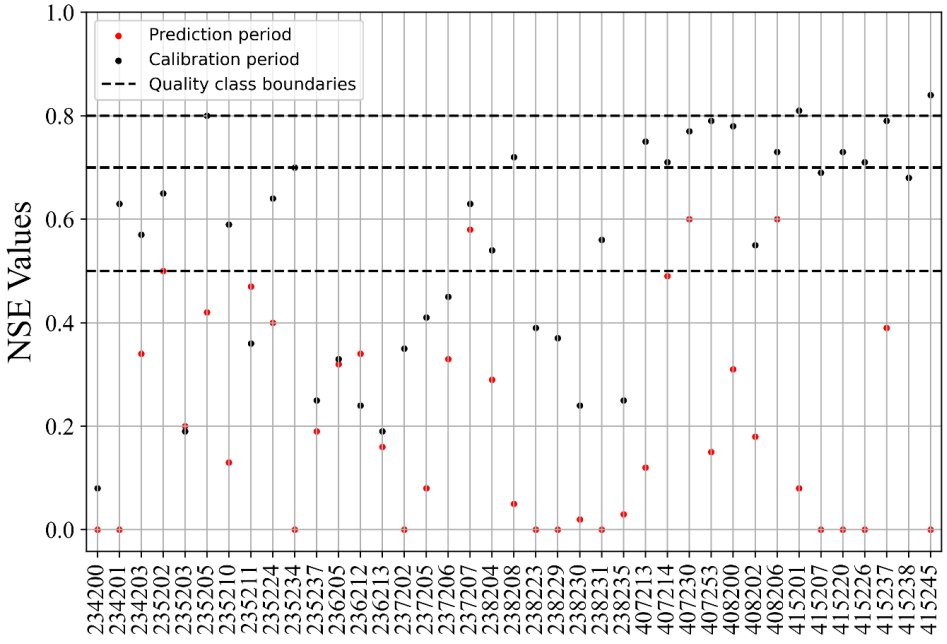


Figure 5 NSE values of the GR4J hydrological model, for the calibration period and prediction of drought and post-drought periods when calibrated to the pre-drought period. The horizontal dashed lines represent the boundary between the performance classes as defined in Table 1. Negative values are shown as zero in this figure.

The performance of the three ML algorithms across the study catchments is presented as the exceedance probability curves in Figure 6. For each value of the NSE in the X-axis, this curve shows the percentage of the sub-catchments that have an NSE value higher than this specific value. A larger area under the curve thus indicates a better model performance and for enhanced clarity, negative values are omitted. None of the models 1, 2a, and 2b show any improvement over the GR4J predictions, whereas for model 2c all ML algorithms lead to a clear improvement. Model 2c is analogous to a deterministic error correction model that uses recent streamflow observations to update GR4J predictions. MLP, Random

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Forest, and Gradient Boosting exhibit consistent improvement for both Model 5 and Model 6 in around 90% of the sub-catchments. MLP exhibits the strong overall performance for all models, which can be attributed to the non-linear nature of the problem, where MLP excels in addressing nonlinearity. To show and compare the performance of models with the best performing ML algorithms in each gauge, box plots of 10 ensemble members are provided in the Appendix, Figure A. 2.

For a better understanding of the behaviour of the eight proposed models, exceedance probability curves depicting mean NSE values are provided in Figure 7. Model 2c demonstrates improvement with respect to GR4J, which emphasises the importance of taking into account short-term streamflow memory. Model 3 shows improvement with respect to model 2c, which indicates the importance of short-term rainfall and streamflow memory and daily rainfall combination. Model 5 and Model 6 clearly outperform Model 3. While model 4 does not show improvement to model 3. This suggests that affecting long-term runoff coefficient to rainfall and short-term rainfall memory can play a crucial role in improving daily streamflow predictions, and therefore the GR4J model would appear to be lacking the ability to represent long-term rainfall-runoff dynamics. Using the MLP algorithm, the performance of Model 5 and Model 6 is relatively similar, indicating that using potential evapotranspiration as a predictor adds little value to the predictions.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

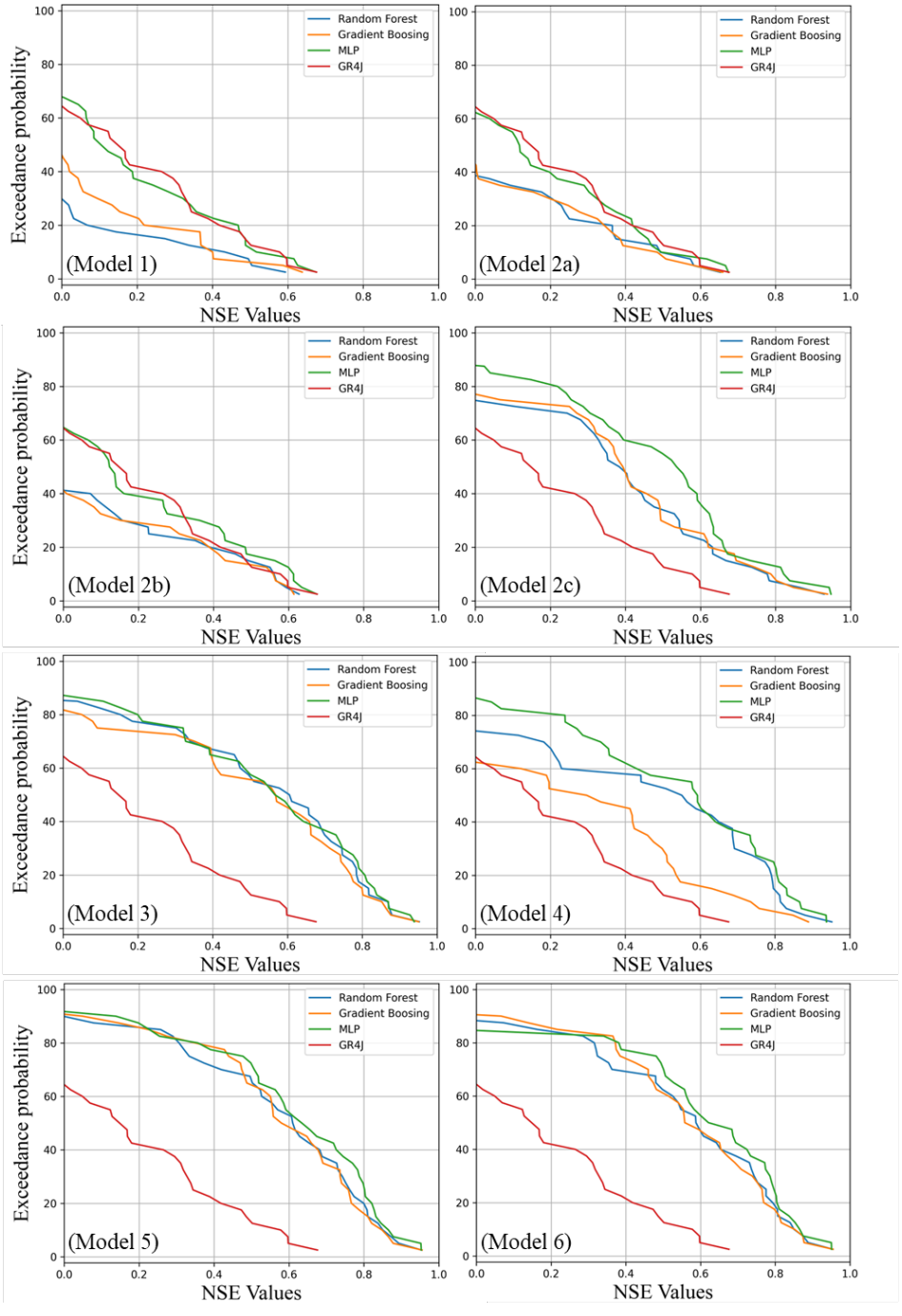


Figure 6 Exceedance probability curves of the mean NSE values for different ML algorithms for All models.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

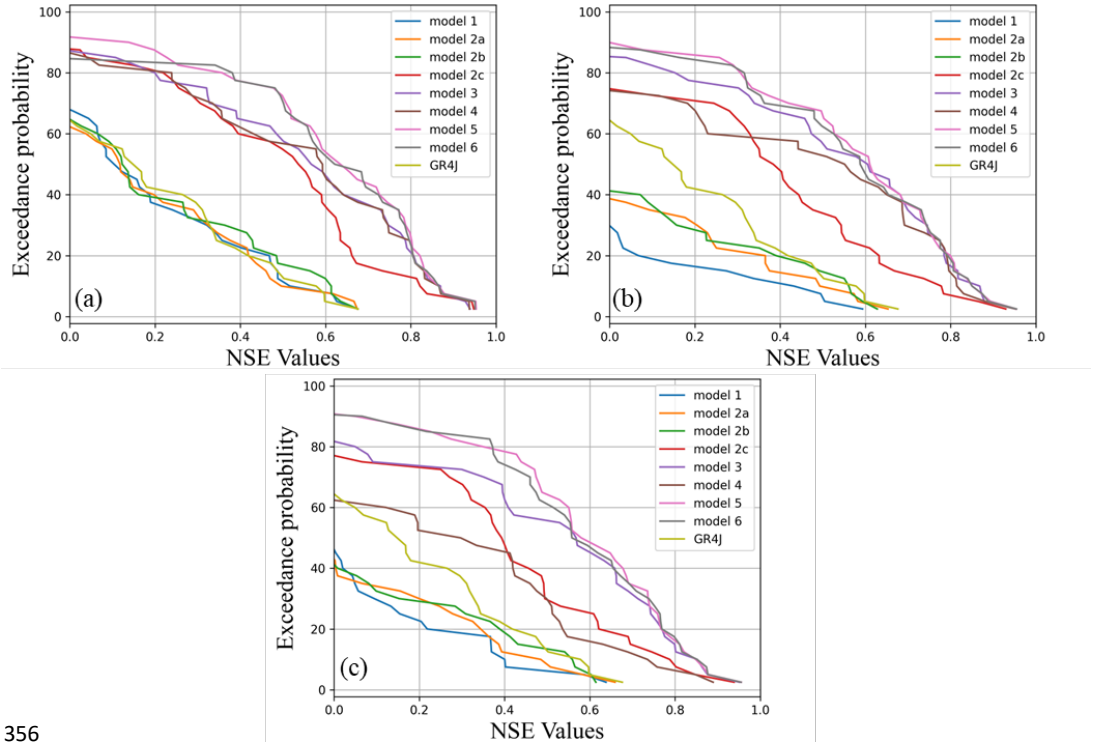


Figure 7 Exceedance probability curves of mean NSE values of different models by application of different algorithms a) MLP, b) Random forest, and c) Gradient boosting.

In some sub-catchments, despite the considerable improvement of the NSE in comparison to GR4J, there are still unsatisfactory results, NSE values less than 0.5 for approximately 30% of sub-catchments, indicating the potential for further enhancement. This suggests that other parameters, such as NDVI, LAI, groundwater exchange, etc., should be considered as predictor in future studies.

The low-flow performance of the ML models assessed in Figure 8 and Figure 9. The exceedance probability curves for the NSE of log-transformed streamflow for the ML models and GR4J results are presented in Figure 8. All ML algorithms produce more accurate low flow predictions than GR4J. In contrast to the results for NSE, Random Forest demonstrates the greatest ability to improve low-flow predictions. Model 2c showed generally better performance compared to the other models when using the MLP algorithm. Models 3, 5, and 6 performed similarly with the Random Forest algorithms and better than models 2c and 4. When Gradient Boosting was applied, both Model 5 and Model 6 yielded

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

similar results, surpassing other models, while model 4 showed very poor performance. These enhancements underscore the effectiveness of machine learning and highlight how predictors and algorithms influence low-flow streamflow predictions. Consequently, it appears that the GR4J model lacks the capability to adequately represent long-term rainfall-runoff and short-term rainfall and runoff dynamics, particularly in the context of low flows.

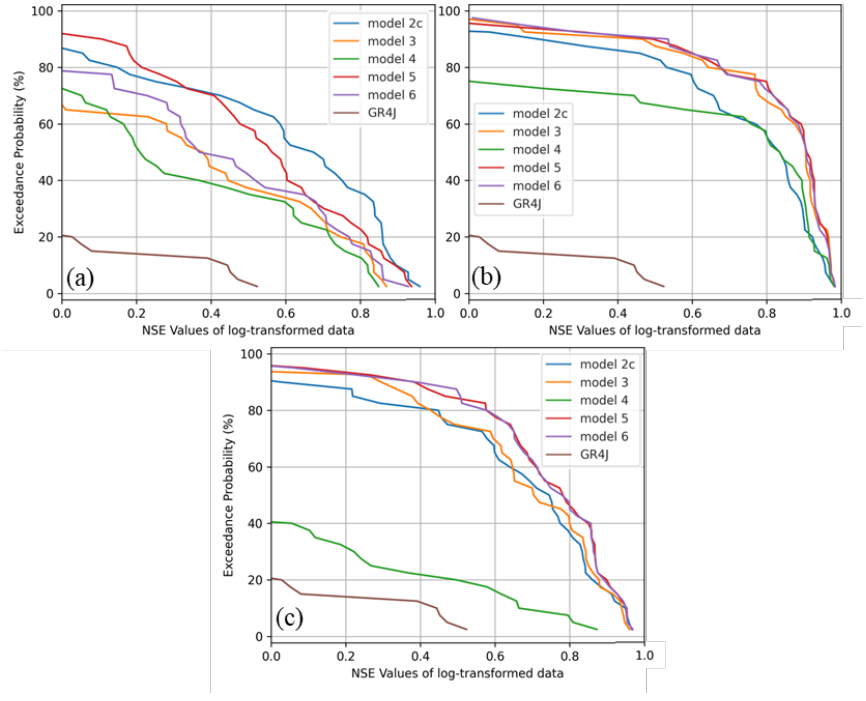


Figure 8 Exceedance probability curves of mean NSE values of log-transformed streamflow, for different models by application of different algorithms a) MLP, b) Random Forest, and c) Gradient boosting.

Figure 9 represents the heatmap of log-transformed observations vs log-transformed predictions for model 3, 5, and 6, as the best performed models. The colour of each cell represents the number of observation-prediction pairs in that cell. Overall, the GR4J model tends to overestimate predictions for lower streamflow. The application of ML algorithms resulted in more symmetrical shape compared to GR4J, with ML predictions more closely following the identity line, indicating improved prediction accuracy. However, in the case of MLP, the darker coloration of cells for log-transformed observations and ML predictions below -4 suggests two issues: the former indicates overestimation of some zero-

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

flow observations, while the latter indicates no-flow predictions for days with actual streamflow. This undesired behaviour was mitigated using other algorithms, with Random Forest demonstrating the best performance among the candidates. Furthermore, the darker and narrower area around the equity line in the Random Forest figures, particularly at lower log-transformed values, highlights significant prediction improvement. However, the difference between models remains indistinct, indicating that while low-flow prediction has improved, it is not evident which predictor has the greatest overall impact. These results underscore the significant influence of applying ML specifically to low-flow conditions, which is the primary focus of this study, i.e., the Millennium drought.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

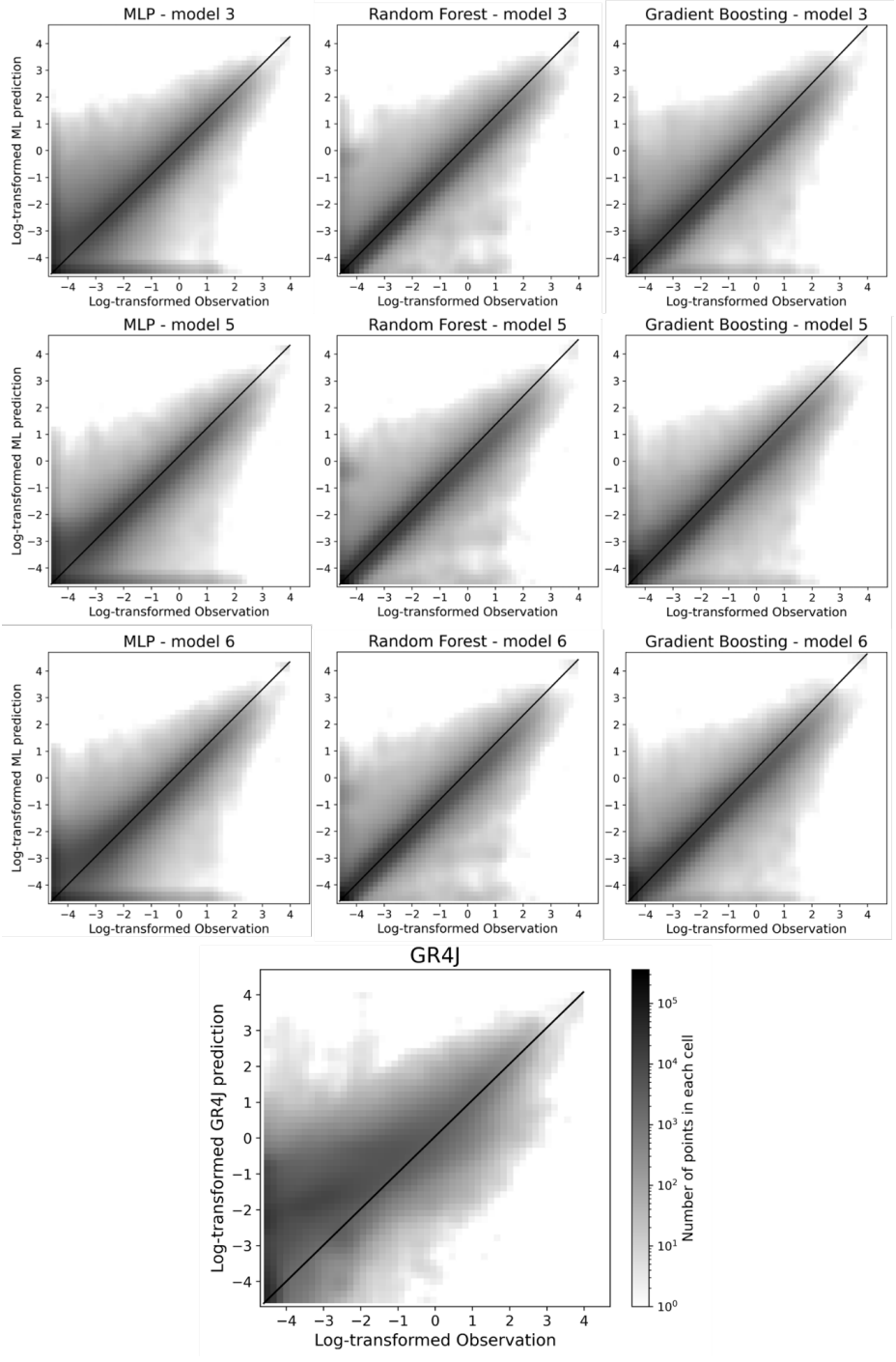


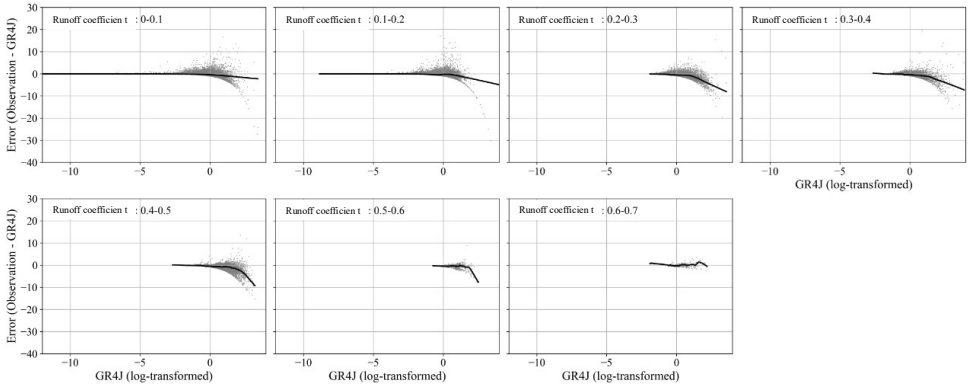
Figure 9 Heatmap of the log-transformation result

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

To better understand the role of long-term runoff coefficient in improving streamflow predictions it is examined how errors in GR4J simulations vary with the long-term runoff coefficient (Figure 10), and how the MLP Model 5, as the best performed model, uses the long-term runoff coefficient to improve streamflow predictions (Figure 11). Overall, the GR4J streamflow simulations cover a wide range of values for all ranges of the long-term runoff coefficient, although few low streamflow values simulated when the long-term runoff coefficient is high. Errors tend to be small for low GR4J streamflow simulations, however for higher streamflow simulations the errors vary with the value of the long-term runoff coefficient. For values of the long-term runoff coefficient (0 to 0.4), GR4J underestimates lower flows and overestimates higher flows. In the 0.4–0.5 range, GR4J predominantly shows overestimations. However, there are no clear patterns for long-term runoff coefficients in the 0.5–0.7 range, where GR4J simulations exhibit small errors. These results indicate that the magnitude of errors in simulated streamflow vary with the long-term runoff coefficient, particularly for simulations of higher streamflow.

The ML method corrects the streamflow simulations to reduce these error patterns, by increasing simulations of large streamflow where the long-term runoff coefficient range (0.0 to 0.4). The ML method makes little correction to streamflow predictions when the long-term runoff coefficient is larger than 0.5. The corrections related to the long-term runoff coefficient being applied by the ML method, to the GR4J simulations, are in addition to corrections related to short-term streamflow memory. Therefore, the results are suggesting that GR4J simulation errors are dependent on the prevailing long-term hydrological conditions, and specifically related to the ability of GR4J to simulate high streamflow during dry conditions. Therefore, the analysis provides insights into structural weaknesses in the GR4J model for the catchments investigated in this study.

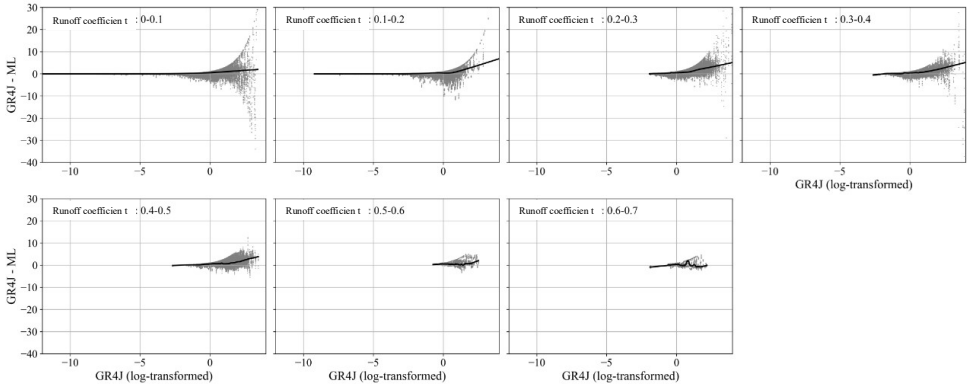
https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025



418

419 *Figure 10 GR4J error categorized based on long-term runoff coefficient ranges. Solid line represents a LOWESS (locally*
420 *weighted scatterplot smoothing) line of best fit.*

421



422

423 *Figure 11 GR4J and ML(MLP model5) difference categorized based on long-term runoff coefficient ranges. Solid line*
424 *represents a LOWESS (locally weighted scatterplot smoothing) line of best fit.*

425

426 Sensitivity analysis of the short-term streamflow memory predictor to the duration over which the
427 predictor is computed indicates that shorter durations lead to slight improvements in NSE values (Figure
428 A. 3). This improvement is likely due to the increased relevance of recent streamflow conditions in
429 error correction and model prediction. In contrast, for the long-term runoff coefficient, the results show
430 no significant differences, and no clear pattern emerges between different durations (Figure A. 4). This
431 lack of consistency suggests that the influence of the long-term runoff coefficient is highly dependent
432 on the specific characteristics of the sub-catchment, with variations observed across different sub-
433 catchments.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

4 Conclusion

This study has investigated streamflow prediction before, during and after the Millennium drought (1997 to 2009) in catchments of Western Victoria, Australia. The GR4J hydrological model was found to produce poor streamflow predictions for the drought and post-drought periods when calibrated to pre-drought conditions. Multiple machine learning methods were used to investigate possible improvements to streamflow predictions, using GR4J model simulations and physical data as predictors. Eight combinations of predictors were considered. All ML algorithms investigated improved the streamflow prediction for the drought and post-drought period in comparison to GR4J when trained using data for the pre-drought period. MLP, Gradient Boosting, and Random Forest produced simulations with greater accuracy overall and for low flow conditions than Linear Regression, Ridge Regression, SVR, and Decision Tree. The better performing ML methods have greater ability to characterise non-linear relationships between predictors and streamflow, than the poorer performing methods, suggesting that the calibrated GR4J model inadequately resolving some non-linear rainfall-runoff processes in the study sub-catchments.

Model 5 that combines predictors representing short-term memories and product of long-term runoff coefficient and rainfall without considering potential evapotranspiration as predictor showed the greatest improvements in prediction accuracy. This model improved streamflow predictions for around 90% of the sub-catchments using MLP, Random Forest, and Gradient Boosting algorithms. The improvements in streamflow predictions arising from the use of long-term runoff coefficient as predictors for the machine learning models suggests that the calibrated GR4J models inadequately represent the slow or long-term dynamics of rainfall-runoff processes. These slow dynamics would therefore appear to be critical for modelling low streamflow, particularly those that occur during drought periods.

In this study, models were training using only data for the pre-drought period that was wetter than the drought and post-drought periods on which their performance was assessed. The calibrated GR4J

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

models showed considerably poorer performance during the drought and post-drought periods. However, the predictions from the ML models, when trained using data for the same period, were able to produce predictions for the drought and post-drought periods that are considerably more accurate than the GR4J model. The better performing ML models used a combination of the GR4J simulations and long-term/short-term variables as predictors. The improved performance of the ML model predictions for the post-drought period relative to those of GR4J, indicate that the long-term and short-term streamflow memory effects exist in the pre-drought period. Therefore, it should be possible to introduce modifications to the GR4J model, used here, to better represent the dynamics related to long-term and short-term variables. It is found that consideration of long-term runoff coefficient and application of ML are most suitable for catchments with low runoff coefficient. As such, this study underscores the important role that ML methods can play in identifying directions for improving models used for streamflow prediction, particularly under variable climatic conditions in drought-prone regions.

Authorship contribution statement

Arash Aghakhani: Conceptualization, Data curation, Formal analysis, Methodology, Investigation, Software, Validation, Writing - original draft, Writing - review & editing

David Robertson: Conceptualization, Data curation, Formal analysis, Methodology, Funding acquisition, Resources, Supervision, Validation, Writing - review & editing

Valentijn Pauwels: Conceptualization, Formal analysis, Methodology, Funding acquisition, Supervision, Validation, Writing - review & editing

Declaration of Competing Interest

"The authors declare that they have no conflict of interest."

Data availability

Code will be available on GitHub. HRS stations data are available at (Hydrologic Reference Stations, 2024)

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Acknowledgement

This work was conducted on the traditional lands of the Boonwurrung peoples of the Kulin Nation. We acknowledge their continuing custodianship of these lands and the rivers that flow through them, and pay our respects to their elders, past and present. We also acknowledge the traditional custodians of the catchments and rivers used in this study. This research has been supported by Monash University and CSIRO.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

5 Appendix

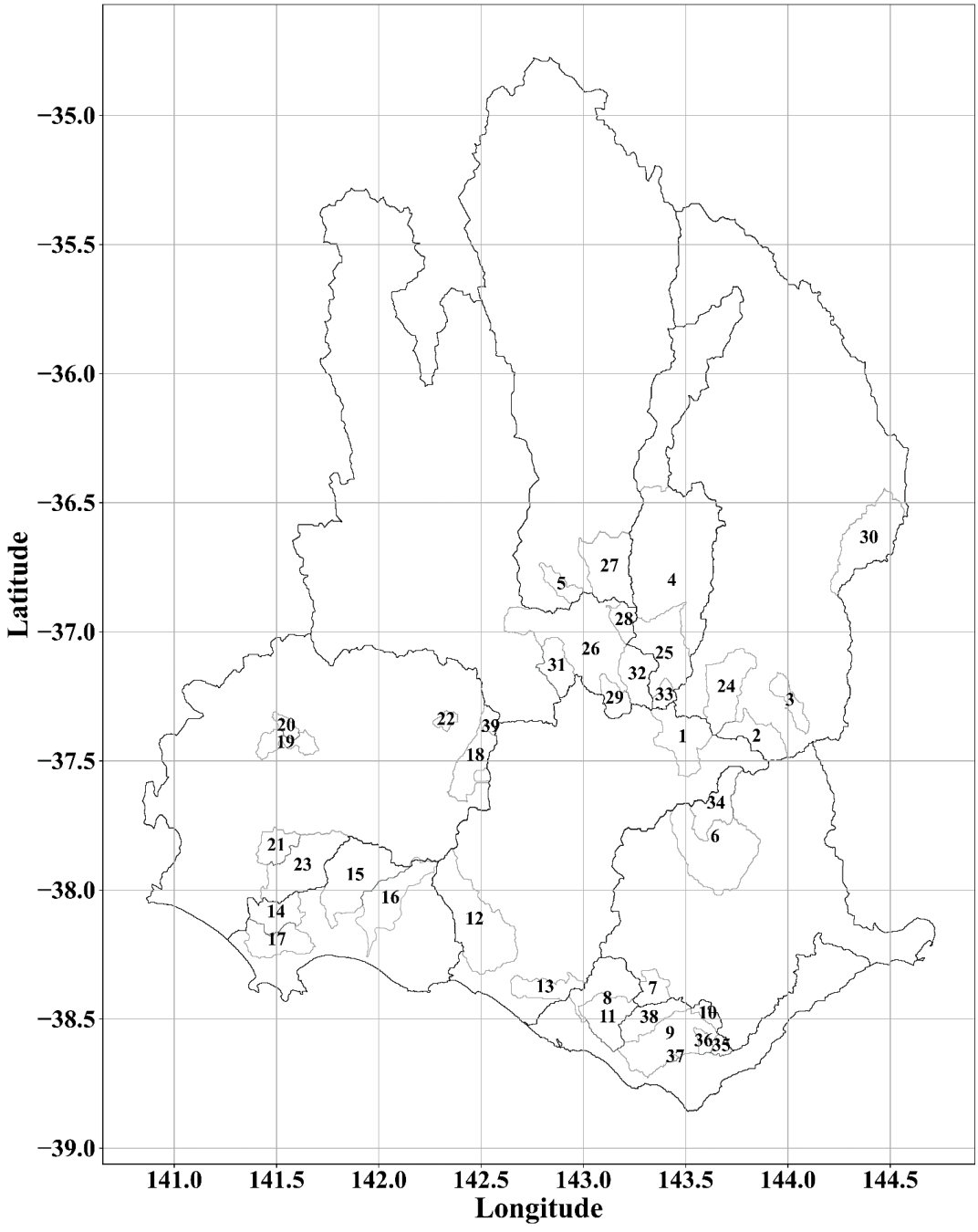


Figure A. 1 Geographical representation of study area

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

494

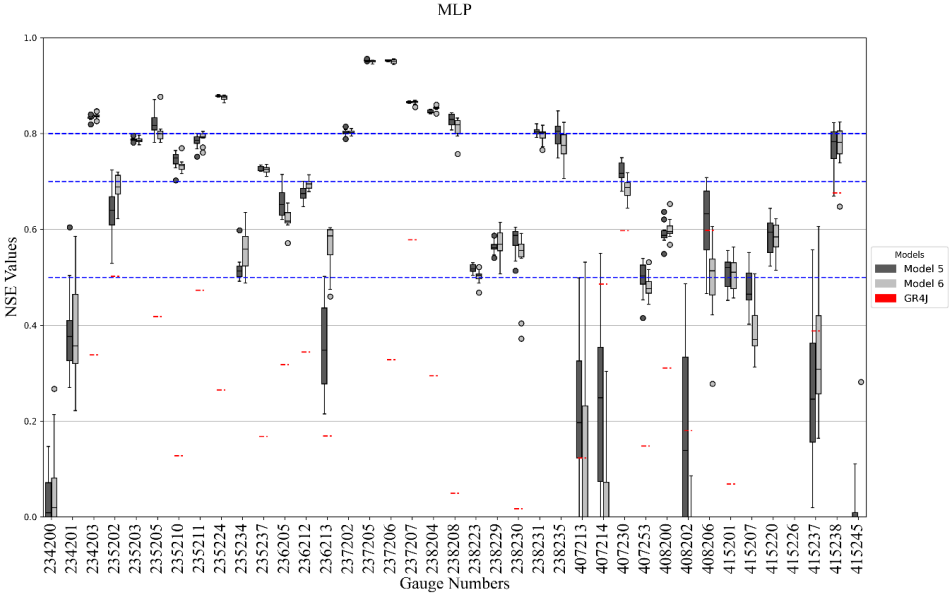
495 *Table A. 1 Sub-catchments general information*

Sub-catchment	Station No.	Gauge Name	Area of sub-catchment (km2)	Catchment Name
1	236213	Mena Park	448.3	Hopkins River
2	407214	Clunes	299.9	Loddon River
3	407230	Strathlea	156	Loddon River
4	408200	Coonooer	2677.3	Avoca River
5	415226	Carrs Plains	124.9	Avon River-Tyrell lake
6	234201	Cressy (Yarima)	1166.5	Barwon River-Lake Corangamite
7	234203	Pirron Yallock (above H'Wy	161.3	Barwon River-Lake Corangamite
8	235203	Curdie	721.3	Otway Coast
9	235224	Burrupa	1042	Otway Coast
10	235234	Gellibrand	76.6	Otway Coast
11	235237	Curdie (Digneys Br)	340.3	Otway Coast
12	236205	Woodford	893.1	Hopkins River
13	236212	Cudgee	225.4	Hopkins River
14	237202	Heywood	268.1	Portland Coast
15	237205	Homerton Br	713.7	Portland Coast
16	237206	Codrington	474	Portland Coast
17	237207	Heathmere	312.4	Portland Coast
18	238204	Dunkeld	384.9	Glenelg River
19	238223	Wando Vale	180.2	Glenelg River
20	238229	Chetwynd	69	Glenelg River
21	238230	Teakettle	197	Glenelg River
22	238231	Big Cord	54	Glenelg River
23	238235	Lower Crawford	600.8	Glenelg River
24	407213	Carisbrook	471.5	Loddon River
25	408206	Archdale Junction	760.6	Avoca River
26	415201	Glenorchy Weir Tail Gauge	1976.1	Wimmera River
27	415220	Wimmera HWY	543	Avon River-Tyrell lake
28	415238	Navarre	139.7	Wimmera River
29	415245	Crowlands	159.2	Wimmera River
30	407253	Minto	652.1	Loddon River
31	415237	Stawell	244.2	Wimmera River
32	415207	Eversley	304.5	Wimmera River

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

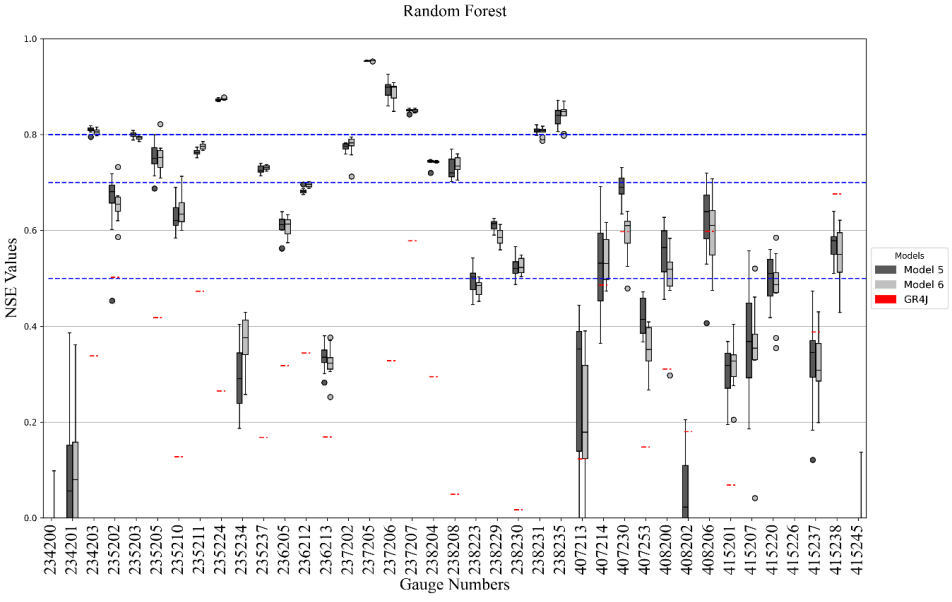
Sub-catchment	Station No.	Gauge Name	Area of sub-catchment (km2)	Catchment Name
33	408202	Amphitheatre	82.6	Avoca River
34	234200	Pitfield	316.9	Barwon River-Lake Corangamite
35	235202	Upper Gelliberand	52.7	Otway Coast
36	235210	Gellibrand	53.9	Otway Coast
37	235205	Wyelangta	4.5	Otway Coast
38	235211	Kennedys Ck	263.7	Otway Coast
39	238208	Jimmy Creek	23.3	Glenelg River

496



497

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025



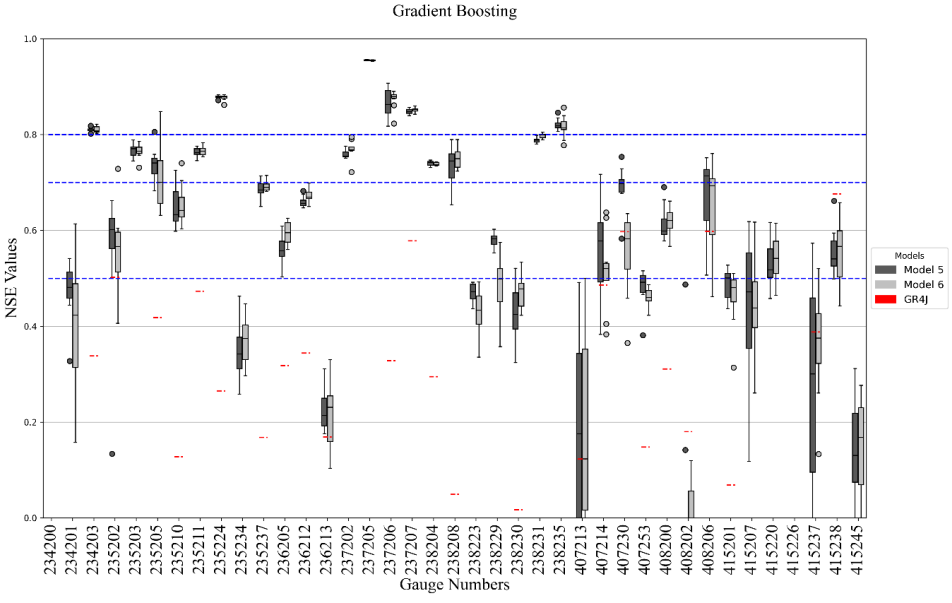


Figure A. 2 box plots of NSE values of 10 repeats

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

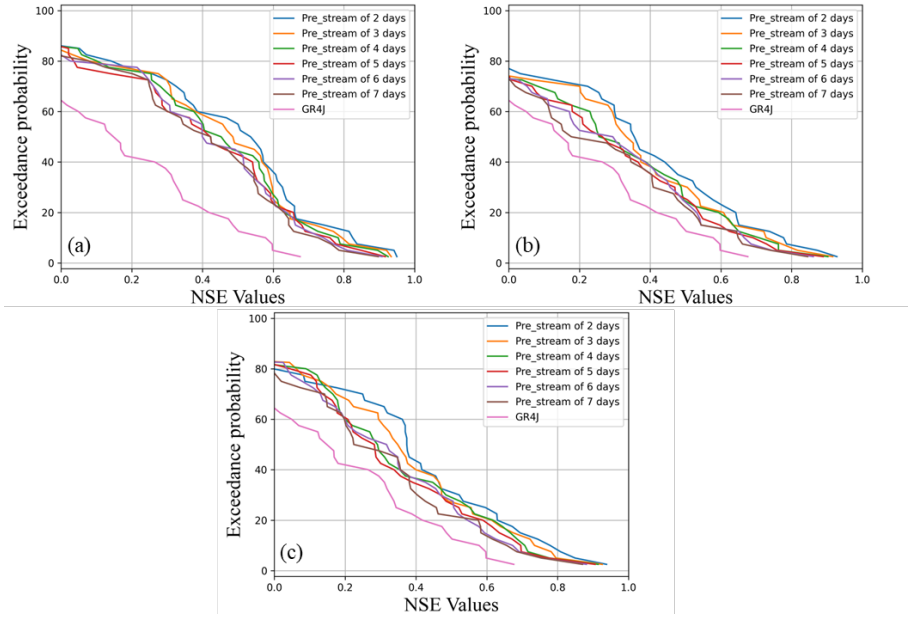


Figure A. 3 Sensitivity analysis of short-term pre-stream (days), a) MLP, b) Random Forest, and c) Gradient boosting.

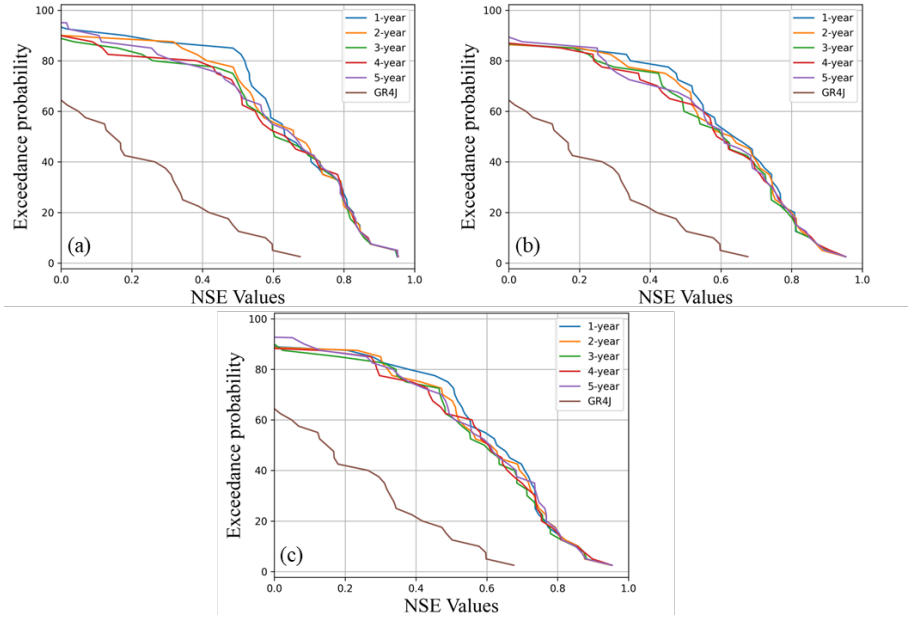


Figure A. 4 Sensitivity analysis of Long-term runoff coefficient (years), a) MLP, b) Random Forest, and c) Gradient boosting

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

6 References

Akusok, A., Bjork, K. M., Miche, Y., and Lendasse, A.: High-Performance Extreme Learning Machines: A Complete Toolbox for Big Data Applications, IEEE Access, 3, https://doi.org/10.1109/ACCESS.2015.2450498, 2015.

Arsenault, R., Breton-Dufour, M., Poulin, A., Dallaire, G., and Romero-Lopez, R.: Streamflow prediction in ungauged basins: analysis of regionalization methods in a hydrologically heterogeneous region of Mexico, Hydrological Sciences Journal, 64, https://doi.org/10.1080/02626667.2019.1639716, 2019.

Aryal, S. K., Zhang, Y., and Chiew, F.: Enhanced low flow prediction for water and environmental management, J Hydrol (Amst), 584, https://doi.org/10.1016/j.jhydrol.2020.124658, 2020.

Ayzel, G., Kurochkina, L., Abramov, D., and Zhuravlev, S.: Development of a regional gridded runoff dataset using long short-term memory (LSTM) networks, Hydrology, 8, https://doi.org/10.3390/hydrology8010006, 2021.

Bentéjac, C., Csörgő, A., and Martínez-Muñoz, G.: A comparative analysis of gradient boosting algorithms, Artif Intell Rev, 54, https://doi.org/10.1007/s10462-020-09896-5, 2021.

Biau, G., Cadre, B., and Rouvière, L.: Accelerated gradient boosting, Mach Learn, 108, https://doi.org/10.1007/s10994-019-05787-1, 2019.

Blöschl, G., Bierkens, M. F. P., Chambel, A., Cudennec, C., Destouni, G., Fiori, A., Kirchner, J. W., McDonnell, J. J., Savenije, H. H. G., Sivapalan, M., Stumpp, C., Toth, E., Volpi, E., Carr, G., Lupton, C., Salinas, J., Széles, B., Viglione, A., Aksoy, H., Allen, S. T., Amin, A., Andréassian, V., Arheimer, B., Aryal, S. K., Baker, V., Bardsley, E., Barendrecht, M. H., Bartosova, A., Batelaan, O., Berghuijs, W. R., Beven, K., Blume, T., Bogaard, T., Borges de Amorim, P., Böttcher, M. E., Boulet, G., Breinl, K., Brilly, M., Brocca, L., Buytaert, W., Castellarin, A., Castelletti, A., Chen, X., Chen, Y., Chen, Y., Chifflard, P., Claps, P., Clark, M. P., Collins, A. L., Croke, B., Dathe, A., David, P. C., de Barros, F. P. J., de Rooij, G., Di Baldassarre, G., Driscoll, J. M., Duethmann, D., Dwivedi, R., Eris, E., Farmer, W. H., Feiccabrino, J., Ferguson, G., Ferrari, E., Ferraris, S., Fersch, B., Finger, D., Foglia, L., Fowler, K., Gartsman, B., Gascoin, S., Gaume, E., Gelfan, A., Geris, J., Gharari, S., Gleeson, T., Glendell, M., Gonzalez Bevacqua, A., González-Dugo, M. P., Grimaldi, S., Gupta, A. B., Guse, B., Han, D., Hannah, D., Harpold, A., Haun, S., Heal, K., Helfricht, K., Herrnegger, M., Hipsey, M., Hlaváčiková, H., Hohmann, C., Holko, L., Hopkinson, C., Hrachowitz, M., Illangasekare, T. H., Inam, A., Innocente, C., Istanbulluoglu, E., Jarihani, B., et al.: Twenty-three unsolved problems in hydrology (UPH)–a community perspective, Hydrological Sciences Journal, 64, https://doi.org/10.1080/02626667.2019.1620507, 2019.

Boucher, M. A., Quilty, J., and Adamowski, J.: Data Assimilation for Streamflow Forecasting Using Extreme Learning Machines and Multilayer Perceptrons, Water Resour Res, 56, https://doi.org/10.1029/2019WR026226, 2020.

Bureau of Meteorology, Previous droughts: http://www.bom.gov.au/climate/drought/knowledge-centre/previous-droughts.shtml, last access: 28 May 2024.

Hydrologic Reference Stations: http://www.bom.gov.au/water/hrs/, last access: 1 February 2024.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Cheng, M., Fang, F., Kinouchi, T., Navon, I. M., and Pain, C. C.: Long lead-time daily and monthly streamflow forecasting using machine learning methods, J Hydrol (Amst), 590, https://doi.org/10.1016/j.jhydrol.2020.125376, 2020.

Chiew, F. H. S., Potter, N. J., Vaze, J., Petheram, C., Zhang, L., Teng, J., and Post, D. A.: Observed hydrologic non-stationarity in far south-eastern Australia: Implications for modelling and prediction, Stochastic Environmental Research and Risk Assessment, 28, https://doi.org/10.1007/s00477-013-0755-5, 2014.

Southwest Victoria alliance-Advocacy Priorities 2021/22: https://treasury.gov.au/sites/default/files/2022-03/258735_southwest_victoria_alliance.pdf, last access: 28 March 2024.

Deo, R. C. and Şahin, M.: An extreme learning machine model for the simulation of monthly mean streamflow water level in eastern Queensland, Environ Monit Assess, 188, https://doi.org/10.1007/s10661-016-5094-9, 2016.

Van Dijk, A. I. J. M., Beck, H. E., Crosbie, R. S., De Jeu, R. A. M., Liu, Y. Y., Podger, G. M., Timbal, B., and Viney, N. R.: The Millennium Drought in southeast Australia (2001-2009): Natural and human causes and implications for water resources, ecosystems, economy, and society, Water Resour Res, 49, https://doi.org/10.1002/wrcr.20123, 2013.

Duan, Q., Sorooshian, S., and Gupta, V. K.: Optimal use of the SCE-UA global optimization method for calibrating watershed models, J Hydrol (Amst), 158, https://doi.org/10.1016/0022-1694(94)90057-4, 1994.

Fowler, K., Peel, M., Saft, M., Peterson, T. J., Western, A., Band, L., Petheram C., Dharmadi, S., Tan, K. S., Zhang, L., and Lane, P.: Explaining changes in rainfall–runoff relationships during and after Australia's Millennium Drought: a community perspective, Hydrology and Earth System Sciences, 26, 6073–6120, 2022.

Fowler, K. J. A., Coxon, G., Freer, J. E., Knoben, W. J. M., Peel, M. C., Wagener, T., Western, A. W., Woods, R. A., and Zhang, L.: Towards more realistic runoff projections by removing limits on simulated soil moisture deficit, J Hydrol (Amst), 600, https://doi.org/10.1016/j.jhydrol.2021.126505, 2021.

Frost, A. J. , and D. P. W.: Evaluation of the Australian landscape water balance model: AWRA-L v6., Melbourne, VIC, Australia, 2018.

Hao, R. and Bai, Z.: Comparative Study for Daily Streamflow Simulation with Different Machine Learning Methods, Water (Switzerland), 15, https://doi.org/10.3390/w15061179, 2023.

He, X., Luo, J., Li, P., Zuo, G., and Xie, J.: A Hybrid Model Based on Variational Mode Decomposition and Gradient Boosting Regression Tree for Monthly Runoff Forecasting, Water Resources Management, 34, https://doi.org/10.1007/s11269-020-02483-x, 2020.

Heberger, M.: Australia's Millennium Drought: Impacts and Responses, in: The World's Water, https://doi.org/10.5822/978-1-59726-228-6_5, 2012.

Jones, D. A., Wang, W., and Fawcett, R.: High-quality spatial climate data-sets for Australia, Australian Meteorological and Oceanographic Journal, 58, https://doi.org/10.22499/2.5804.003, 2009.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

584 Konapala, G., Kao, S. C., Painter, S. L., and Lu, D.: Machine learning assisted hybrid models can
585 improve streamflow simulation in diverse catchments across the conterminous US, Environmental
586 Research Letters, 15, https://doi.org/10.1088/1748-9326/aba927, 2020.

587 Kumar, V., Kedam, N., Sharma, K. V., Mehta, D. J., and Caloiero, T.: Advanced Machine Learning
588 Techniques to Improve Hydrological Prediction: A Comparative Analysis of Streamflow Prediction
589 Models, Water (Switzerland), 15, https://doi.org/10.3390/w15142572, 2023.

590 Lees, T., Buechel, M., Anderson, B., Slater, L., Reece, S., Coxon, G., and Dadson, S. J.: Benchmarking
591 data-driven rainfall-runoff models in Great Britain: A comparison of long short-term memory (LSTM)-
592 based models with four lumped conceptual models, Hydrol Earth Syst Sci, 25,
593 https://doi.org/10.5194/hess-25-5517-2021, 2021.

594 Li, M., Zhang, Y., Wallace, J., and Campbell, E.: Estimating annual runoff in response to forest change:
595 A statistical method based on random forest, J Hydrol (Amst), 589,
596 https://doi.org/10.1016/j.jhydrol.2020.125168, 2020.

597 Lima, A. R., Cannon, A. J., and Hsieh, W. W.: Forecasting daily streamflow using online sequential
598 extreme learning machines, J Hydrol (Amst), 537, https://doi.org/10.1016/j.jhydrol.2016.03.017,
599 2016.

600 Mohammadi, B., Ahmadi, F., Mehdizadeh, S., Guan, Y., Pham, Q. B., Linh, N. T. T., and Tri, D. Q.:
601 Developing Novel Robust Models to Improve the Accuracy of Daily Streamflow Modeling, Water
602 Resources Management, 34, https://doi.org/10.1007/s11269-020-02619-z, 2020.

603 Moosavi, V., Gheisoori Fard, Z., and Vafakhah, M.: Which one is more important in daily runoff
604 forecasting using data driven models: Input data, model type, preprocessing or data length?, J Hydrol
605 (Amst), 606, https://doi.org/10.1016/j.jhydrol.2022.127429, 2022.

606 Moriasi, D. N., Gitau, M. W., Pai, N., and Daggupati, P.: Hydrologic and water quality models:
607 Performance measures and evaluation criteria, Trans ASABE, 58,
608 https://doi.org/10.13031/trans.58.10715, 2015.

609 Ng, K. W., Huang, Y. F., Koo, C. H., Chong, K. L., El-Shafie, A., and Najah Ahmed, A.: A review of hybrid
610 deep learning applications for streamflow forecasting, J Hydrol (Amst), 625, 130141,
611 https://doi.org/10.1016/j.jhydrol.2023.130141, 2023.

612 Onyari, E. and Ilunga, F.: Application of MLP neural network and M5P model tree in predicting
613 streamflow: A case study of Luvuvhu catchment, South Africa, ijimt.org, 2013.

614 Perraud, J. M., Bennett, J. C., Bridgart, R., and Robertson, D.: SWIFT2: Advanced software for
615 continuous ensemble short-term streamflow forecasting, in: The Art and Science of Water - 36th
616 Hydrology and Water Resources Symposium, HWRS 2015, 2015.

617 Perrin, C., Michel, C., and Andréassian, V.: Improvement of a parsimonious model for streamflow
618 simulation, J Hydrol (Amst), 279, https://doi.org/10.1016/S0022-1694(03)00225-7, 2003.

619 Peterson, T. J., Saft, M., Peel, M. C., and John, A.: Watersheds may not recover from drought, Science
620 (1979), 372, https://doi.org/10.1126/science.abd5085, 2021.

621 Petty, T. R. and Dhingra, P.: Streamflow Hydrology Estimate Using Machine Learning (SHEM), J Am
622 Water Resour Assoc, 54, https://doi.org/10.1111/1752-1688.12555, 2018.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Pham, L. T., Luo, L., and Finley, A.: Evaluation of random forests for short-term daily streamflow forecasting in rainfall- And snowmelt-driven watersheds, Hydrol Earth Syst Sci, 25, https://doi.org/10.5194/hess-25-2997-2021, 2021.

Pradhan, P., Tingsanchali, T., and Shrestha, S.: Evaluation of Soil and Water Assessment Tool and Artificial Neural Network models for hydrologic simulation in different climatic regions of Asia, Science of the Total Environment, 701, https://doi.org/10.1016/j.scitotenv.2019.134308, 2020.

Rahimzad, M., Moghaddam Nia, A., Zolfonoon, H., Soltani, J., Danandeh Mehr, A., and Kwon, H. H.: Performance Comparison of an LSTM-based Deep Learning Model versus Conventional Machine Learning Algorithms for Streamflow Forecasting, Water Resources Management, 35, https://doi.org/10.1007/s11269-021-02937-w, 2021.

Reis, G. B., da Silva, D. D., Fernandes Filho, E. I., Moreira, M. C., Veloso, G. V., Fraga, M. de S., and Pinheiro, S. A. R.: Effect of environmental covariable selection in the hydrological modeling using machine learning models to predict daily streamflow, J Environ Manage, 290, https://doi.org/10.1016/j.jenvman.2021.112625, 2021.

van Rensch, P., Turner, M., Saft, M., Peel, M. C., Peterson, T. J., Hope, P., and Pepler, A.: The Role of Weather System Changes and Catchment Characteristics in the Rainfall-Runoff Relationship Shift in Victoria, Australia, Water Resour Res, 59, https://doi.org/10.1029/2022wr033692, 2023.

Robertson, D. E., Zheng, H., Peña-Arancibia, J. L., Chiew, F. H. S., Aryal, S., Malerba, M., and Wright, N.: How sensitive are catchment runoff estimates to on-farm storages under current and future climates?, J Hydrol (Amst), 626, https://doi.org/10.1016/j.jhydrol.2023.130185, 2023.

Romanowicz, R. J.: Data based mechanistic model for low flows: Implications for the effects of climate change, J Hydrol (Amst), 336, https://doi.org/10.1016/j.jhydrol.2006.12.015, 2007.

Roy, M. H. and Larocque, D.: Robustness of random forests for regression, J Nonparametr Stat, 24, https://doi.org/10.1080/10485252.2012.715161, 2012.

Rozos, E., Dimitriadis, P., and Bellos, V.: Machine learning in assessing the performance of hydrological models, Hydrology, 9, https://doi.org/10.3390/hydrology9010005, 2022.

Saft, M., Western, A. W., Zhang, L., Peel, M. C., and Potter, N. J.: The influence of multiyear drought on the annual rainfall-runoff relationship: An Australian perspective, Water Resour Res, 51, https://doi.org/10.1002/2014WR015348, 2015.

Slater, L. J., Anderson, B., Buechel, M., Dadson, S., Han, S., Harrigan, S., Kelder, T., Kowal, K., Lees, T., Matthews, T., Murphy, C., and Wilby, R. L.: Nonstationary weather and water extremes: A review of methods for their detection, attribution, and management, https://doi.org/10.5194/hess-25-3897-2021, 2021.

Primary Production Landscapes of Victoria - Northwest Victoria: https://vro.agriculture.vic.gov.au/dpi/vro/vrosite.nsf/pages/primary_prod_landscapes_nw_vic, last access: 28 March 2024.

Stephens, C. M., Marshall, L. A., and Johnson, F. M.: Investigating strategies to improve hydrologic model performance in a changing climate, J Hydrol (Amst), 579, https://doi.org/10.1016/j.jhydrol.2019.124219, 2019.

Szczepanek, R.: Daily Streamflow Forecasting in Mountainous Catchment Using XGBoost, LightGBM and CatBoost, Hydrology, 9, https://doi.org/10.3390/hydrology9120226, 2022.

https://doi.org/10.5194/egusphere-2025-553
Preprint. Discussion started: 13 March 2025

Tongal, H. and Booij, M. J.: Simulation and forecasting of streamflows using machine learning models coupled with base flow separation, J Hydrol (Amst), 564, https://doi.org/10.1016/j.jhydrol.2018.07.004, 2018.

Wallis, A. M., Graymore, M. L. M., and Richards, A. J.: Significance of environment in the assessment of sustainable development: The case for south west Victoria, Ecological Economics, 70, https://doi.org/10.1016/j.ecolecon.2010.11.010, 2011.

Wang, K., Band, S. S., Ameri, R., Biyari, M., Hai, T., Hsu, C. C., Hadjouni, M., Elmannai, H., Chau, K. W., and Mosavi, A.: Performance improvement of machine learning models via wavelet theory in estimating monthly river streamflow, Engineering Applications of Computational Fluid Mechanics, 16, https://doi.org/10.1080/19942060.2022.2119281, 2022.

Worland, S. C., Farmer, W. H., and Kiang, J. E.: Improving predictions of hydrological low-flow indices in ungaged basins using machine learning, Environmental Modelling and Software, 101, https://doi.org/10.1016/j.envsoft.2017.12.021, 2018.

Yaseen, Z. M., El-shafie, A., Jaafar, O., Afan, H. A., and Sayl, K. N.: Artificial intelligence based models for stream-flow forecasting: 2000-2015, https://doi.org/10.1016/j.jhydrol.2015.10.038, 2015.

Yaseen, Z. M., Jaafar, O., Deo, R. C., Kisi, O., Adamowski, J., Quilty, J., and El-Shafie, A.: Stream-flow forecasting using extreme learning machines: A case study in a semi-arid region in Iraq, J Hydrol (Amst), 542, https://doi.org/10.1016/j.jhydrol.2016.09.035, 2016.

Yeturu, K.: Machine learning algorithms, applications, and practices in data science, in: Handbook of Statistics, vol. 43, https://doi.org/10.1016/bs.host.2020.01.002, 2020.

Zhang, X. S., Amirthanathan, G. E., Bari, M. A., Laugesen, R. M., Shin, D., Kent, D. M., MacDonald, A. M., Turner, M. E., and Tuteja, N. K.: How streamflow has changed across Australia since the 1950s: Evidence from the network of hydrologic reference stations, Hydrol Earth Syst Sci, 20, https://doi.org/10.5194/hess-20-3947-2016, 2016.

Zheng, H., Chiew, F. H. S., Post, D. A., Robertson, D. E., Charles, S. P., Grose, M. R., and Potter, N. J.: Projections of future streamflow for Australia informed by CMIP6 and previous generations of global climate models, J Hydrol (Amst), 636, 131286, https://doi.org/https://doi.org/10.1016/j.jhydrol.2024.131286, 2024.