

## Article

# Development of Multi-Inflow Prediction Ensemble Model Based on Auto-Sklearn Using Combined Approach: Case Study of Soyang River Dam

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**Abstract:** Accurate prediction of dam inflows is essential for effective water resource management and dam operation. In this study, we developed a multi-inflow prediction ensemble (MPE) model for dam inflow prediction using auto-sklearn (AS). The MPE model is designed to combine ensemble models for high and low inflow prediction and improve dam inflow prediction accuracy. We investigated the impact of datasets assigned to flow regimes on the ensemble composition and compared the performance of the MPE model to an AS-based ensemble model developed using a conventional approach. Our findings showed that the MPE model outperformed the conventional model in predicting dam inflows during flood and nonflood periods, reducing the root mean square error (RMSE) and mean absolute error (MAE) by 22.1% and 24.9% for low inflows, and increasing the coefficient of determination ( $R^2$ ) and Nash–Sutcliffe efficiency (NSE) by 21.9% and 35.8%, respectively. These results suggest that the MPE model has the potential to improve water resource management and dam operation, benefiting both the environment and society. Overall, the methodology of this study is expected to contribute to the development of a robust ensemble model for dam inflow prediction in regions with high climate variability.

**Keywords:** dam inflow prediction; ensemble; auto-sklearn; combined approach; multi-inflow prediction ensemble



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## 1. Introduction

The real-time management of water resources in arid and semiarid regions is facing a significant challenge due to the frequent occurrence of floods and droughts caused by climate change [1–3]. To address these challenges, many countries have constructed and operated multipurpose dams to stabilize the water supply and control floods [4]. However, the increased variability in the inflow to dams due to changes in climate and land use directly impacts the water level calculation and dam operation [5]. This can cause significant downstream damage from uncontrolled discharge during flood seasons, and make it difficult to ensure the minimum water supplies essential for water quality and aquatic environments during dry seasons [6]. Hence, accurate prediction of dam inflow is critical for effective water resource management and dam operations.

There are two major approaches to modeling studies for dam (or reservoir) inflow prediction: physical or conceptual models [7–11] and data-driven machine learning (ML) models [12–16]. Physical models are effective in simulating hydrologic processes but

require in-depth knowledge and calibration [17], while conceptual models have lower data requirements and computational complexity but may be limited by the lack of detailed physical information. Recently, ML models have become more popular for dam inflow prediction due to their simplicity, low data requirements, and robustness [18]. ML models can quickly capture the complexity of dam inflow time-series data without extensive prior knowledge [19]. In addition, many studies have successfully utilized ensemble methods to improve the accuracy of dam inflow predictions [20–23]. Ensemble modeling is a process in which an ML model combines the predictive capabilities of individual base models unique to the model to generate generalized predictions, allowing for capturing various aspects of the data and providing high prediction performance. However, developing effective ensembles requires a deep understanding of model selection, combination, and hyperparameter optimization. These tasks are often laborious and time-consuming, and there is a risk of human error that can affect the reliability and validity of model predictions.

Automated machine learning (AutoML) can be used as an alternative for developing ensemble models. AutoML can automatically generate various ML models and effectively create an ensemble model by combining them to perform more accurate predictions [24]. It can reduce the risk of human error and increase the reliability of the ensemble model's predicted values. Its greatest advantage is that it helps save time and effort in selecting ML models and optimizing them without requiring specialized domain knowledge. According to several studies, AutoML can effectively generate satisfactory results for various types of datasets [25–28]. Despite the success of AutoML in generating satisfactory results for various types of datasets, its performance in dam inflow prediction has not been evaluated.

The dam inflow is greatly influenced by various factors such as precipitation, vegetation, soil, and human activities. In particular, the pattern of dam inflow in regions with high climate variability can show significant differences between rainy and nonrainy seasons [29]. The complex and nonlinear characteristics of data can affect not only the data preprocessing methods of AutoML but also the selection of ensemble models and hyperparameter combinations. Therefore, the development of ensemble models that consider the characteristics of the flow regime is necessary for the accurate prediction of dam inflow. Hong et al. [30] showed that an ensemble of ML models that consider the characteristics of high and low inflow data can improve the limitations of flow regime and rainfall on inflow prediction compared to using a single ML model. Moon et al. [31] developed a flow regime-based ANFIS dam inflow prediction (FADIP) model, which is based on the adaptive neuro-fuzzy inference system (ANFIS), and compared it with an ANFIS dam inflow prediction (ADIP) model. Their results showed that FADIP outperformed ADIP in accuracy throughout the entire period, especially in predicting dam inflow during the normal and low flow seasons. Furthermore, appropriate dataset construction for hydrological flow regimes can alleviate the issue of data imbalance and prediction model generalization by contributing to the learning of various aspects of the data. Zhang et al. [32] demonstrated that a multiclass dataset construction for dam inflow strategies according to different flow regimes can effectively handle high-dimensional data and improve the overall prediction accuracy of ensemble models. Choi et al. [33] demonstrated that applying seasonal division and normalization to dam inflow training data can contribute to reducing errors caused by data deviation and improving the learning accuracy of the multilayer perceptron (MLP) model. However, the impact of datasets assigned to flow regimes on the ensemble composition based on AutoML for dam inflow prediction and its effect on improving ensemble model performance have not been quantified.

Therefore, this study aims to evaluate the performance of an automated machine learning (AutoML) approach for developing a multi-inflow prediction ensemble (MPE) model for dam inflow prediction, which has not been previously evaluated in previous studies. The novelty of this study is that the MPE model trains independent ensemble models for high and low inflow prediction based on auto-sklearn (AS) and combines their predictions, taking into account the characteristics of the hydrological flow regime.

The hypothesis is that the MPE model combining the AS-based approach outperforms the conventional AS-based ensemble model by effectively capturing the complex and nonlinear characteristics of dam inflow time-series data in both flood and nonflood periods.

The main objectives of this study are to develop the MPE model, evaluate its performance by comparing it to a conventional AS-based ensemble model, quantify the impact of datasets assigned to flow regimes on the ensemble composition based on AutoML and provide insight into developing an AS-based robust ensemble model for predicting dam inflow. The methodology of this study is expected to contribute to sustainable water resource management and dam operations in regions with high climate variability.

## 2. Materials and Methods

### 2.1. Description of the Study Area

The Soyang River Dam (SRD) in South Korea, located between  $37^{\circ}40'$  to  $38^{\circ}30'$  N and  $127^{\circ}40'$  to  $128^{\circ}40'$  E, is a crucial structure that plays a key role in controlling floods and droughts in the downstream area (Figure 1). The SRD has a  $70 \text{ km}^2$  reservoir area and supplies an average of 1.213 million  $\text{m}^3$  of water annually for residential, industrial, and irrigation use in the capital area. The  $2703 \text{ km}^2$  basin has an elevation range of 80–1693 m and is primarily composed of forest (89.5%), with smaller portions of agricultural land (5.7%), water (2.4%), and other lands (2.4%) [30]. The SRD is challenged by the large monthly variations in mean annual precipitation and dam inflow due to the Asian monsoon climate, making it difficult to manage water resources in downstream areas and establish an effective operational strategy (Figure 2). This situation is further complicated by the potential for frequent floods and droughts caused by seasonal fluctuations in precipitation due to climate change [34].

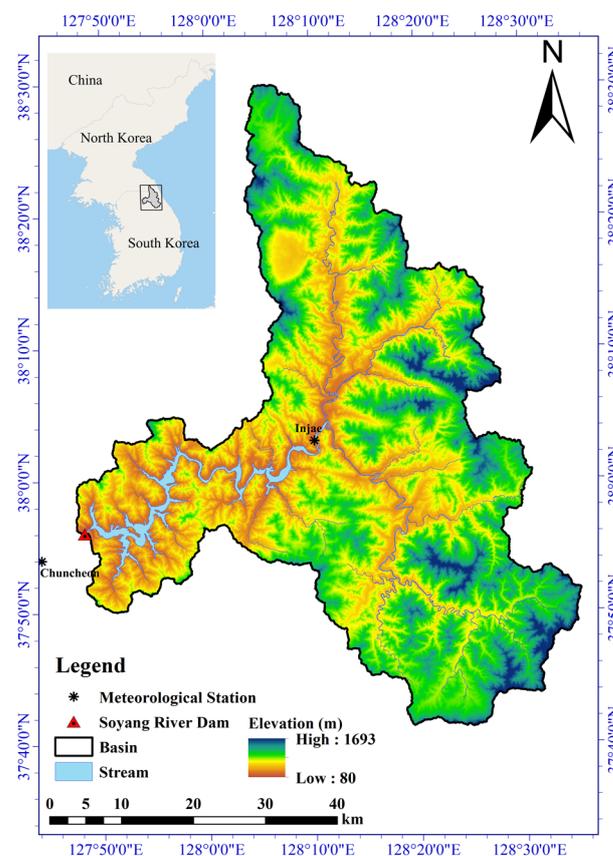
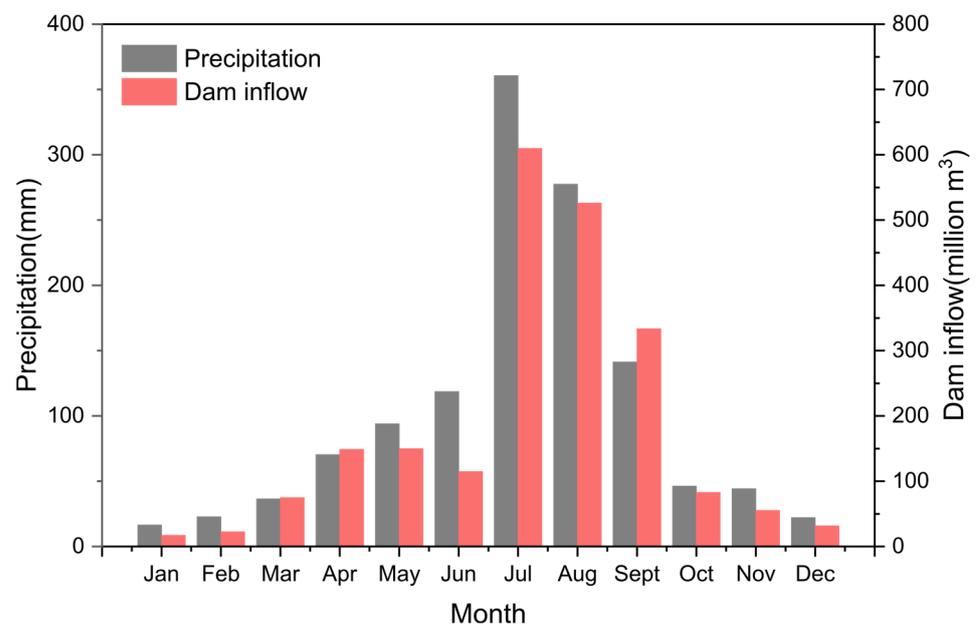


Figure 1. Study area.



**Figure 2.** Average annual precipitation and dam inflow in the study area.

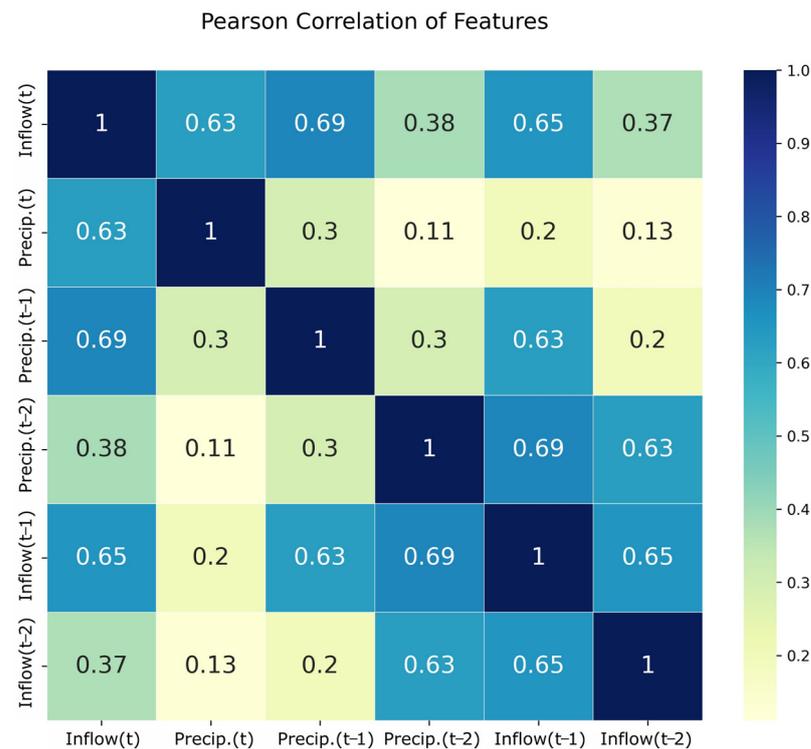
## 2.2. Data Collection

The flow into a dam can be influenced by various factors, including precipitation, temperature, evapotranspiration, land use, and anthropogenic activities [35]. However, it can be challenging to establish a relationship between these factors and the dam inflow. In addition, using all of these factors as input data for ML models can lead to difficulties in data preprocessing and collection. Mao et al. [36] found that dam inflow (i.e., streamflow) depends more strongly on variation in precipitation than temperature and evapotranspiration. In addition, Hong et al. [30] took into account the effect of prior weather conditions when predicting daily dam inflow using ML models by using weather and inflow data from the past one and two days. In this study, precipitation (Chuncheon and Injae stations) and SRD inflow data for 40 years (1980–2019) were obtained from the Korea Meteorological Administration (<https://data.kma.go.kr>, accessed on 31 March 2023) and Water Resources Management Information System (<https://www.wamis.go.kr>, accessed on 31 March 2023), respectively. The precipitation on the current day ( $P_t$ ) and the precipitation ( $P_{t-1}$  and  $P_{t-2}$ ) and inflow data ( $I_{t-1}$  and  $I_{t-2}$ ) one and two days earlier were used as input for AS models to predict dam inflow ( $I_t$ ). The heat map in Figure 3 shows the correlation for each input factor. The precipitation one day earlier ( $P_{t-1}$ ) is most strongly correlated with the inflow on the day, followed by  $I_{t-1}$ ,  $P_{t-1}$ ,  $P_{t-2}$ , and  $I_{t-2}$ . Based on these input factors, the models were trained and validated using 35 years of data (1980–2015), and their predictive ability was tested using three years of data (2016–2019). Table 1 shows the details of the dataset used in the study.

**Table 1.** Dataset used to develop AS ensemble model.

Model	Input Variables	Target Variable	Period
Training and validation dataset ( $n = 13,148$ )	$I_{t-1}, I_{t-2}$ $P_t, P_{t-1}, P_{t-2}$	$I_t$	1980–2015
Test dataset ( $n = 1461$ )	$I_{t-1}, I_{t-2}$ $P_t, P_{t-1}, P_{t-2}$	$I_t$	2016–2019

$t$ : time (day) index.



**Figure 3.** Heat map showing correlation for each input factor.

### 2.3. Auto-Sklearn

AS is an AutoML framework based on the scikit-learn library that automates the process of finding the optimal ML pipeline for solving classification and regression problems within a limited time frame. The framework includes a total of 15 models, 14 feature preprocessing methods, and 4 data preprocessing methods.

To create an ensemble model, AS utilizes three techniques: meta-learning, Bayesian optimization, and ensemble selection. The meta-learning process in AS uses information from 140 pretrained reference datasets from OpenML to determine the best combination of models and hyperparameters for a given dataset [28]. During this process, the algorithm generates initial good hyperparameter configurations based on previous runs. By starting from these promising configurations, which have shown good performance on similar datasets, the efficiency of hyperparameter optimization can be significantly improved, resulting in a more accurate model [37].

After the meta-learning process, Bayesian optimization is applied to further refine the hyperparameters of top-performing models identified during meta-learning. This optimization algorithm, which uses Bayesian theory and a Gaussian process, is more efficient in finding the optimal hyperparameters by reducing the number of unnecessary configurations [38]. Finally, AS employs an ensemble selection technique [39] to create the final ensemble model, which is a combination of the top-performing models with varying weights, as determined by comparing their accuracy. The workflow of AS is illustrated in Figure 4.

### 2.4. MPE Model Development Using Split Datasets

Figure 5 illustrates the development of the MPE model using a combined approach with an AS. The combined approach trains two ensemble models using datasets separated by high and low inflow conditions, and the dam inflow is predicted by integrating the results. In contrast, the conventional approach trains an ensemble model using the whole training dataset and evaluates its performance on the test set.

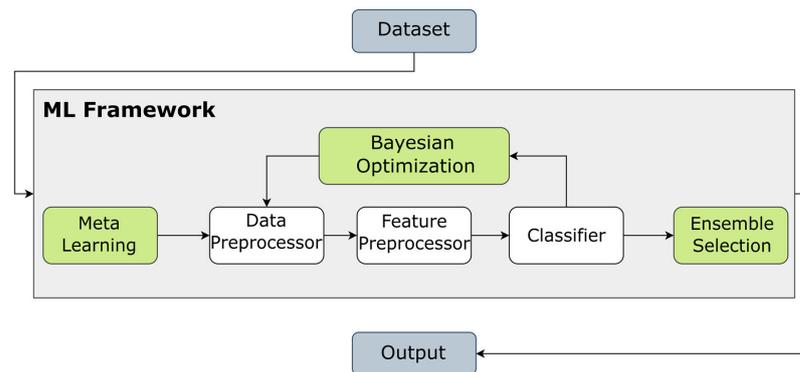


Figure 4. Workflow of AS.

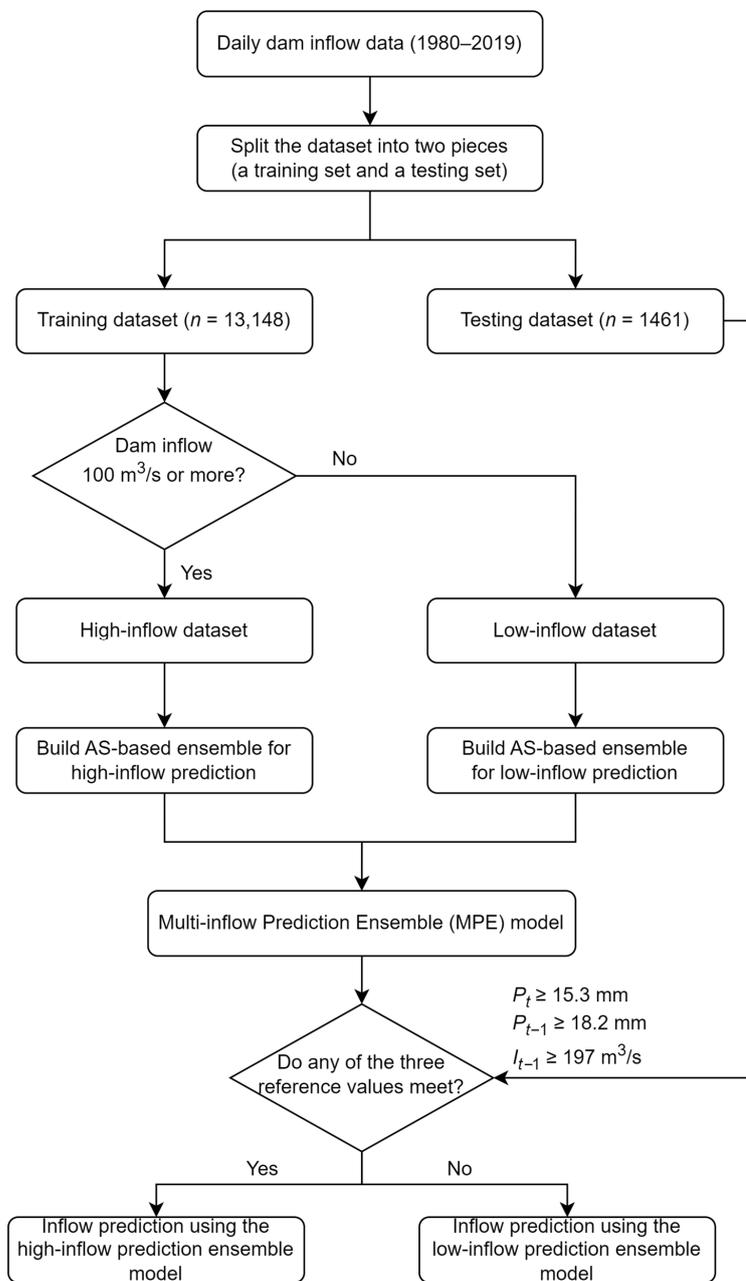


Figure 5. Development of the MPE model.

In this study, to build the MPE model, the whole training dataset was divided into high and low inflow datasets using a high-inflow reference value of  $100 \text{ m}^3/\text{s}$ , as suggested by Hong et al. [30]. Then, input factors highly correlated with inflow (i.e., precipitation on the day ( $P_t$ ), precipitation from one day earlier ( $P_{t-1}$ ), and inflow from one day earlier ( $I_{t-1}$ )) were selected to determine the high-inflow reference value for the test set. The average and median values of these three factors for high-inflow ( $\geq 100 \text{ m}^3/\text{s}$ ) in the whole training dataset were used to determine the high-inflow reference values. The reference values for  $P_t$  and  $P_{t-1}$  were found to be 15.3 and 18.2 mm, respectively, based on the average value. The reference value for  $I_{t-1}$ , which showed a large deviation, was determined to be  $197.4 \text{ m}^3/\text{s}$  using the median value.

These values are used to determine whether the MPE model will use an ensemble model for unique prediction or an ensemble model for low-flow prediction when given new input data for predicting dam inflow in the MPE model. In other words, the MPE model predicts the dam inflow by using the high-inflow prediction model if any of the three reference values ( $P_t$ ,  $P_{t-1}$ , and  $I_{t-1}$ ) are met in the test set; otherwise, the low-inflow prediction model is used. In both the conventional and combined approaches, the `time_left_for_this_task` and `per_run_time_limit` parameters of AS were set to 1 h and 360 s, respectively. The AS-based ensemble models developed through these two approaches were validated using 10-fold cross-validation, and their predictive performance was compared on the test set.

### 2.5. Performance Evaluation Metrics

In this study, we used the coefficient of determination ( $R^2$ ), Nash–Sutcliffe efficiency ( $NSE$ ), root mean square errors ( $RMSE$ ), and mean absolute error ( $MAE$ ) to evaluate the predictive performance of the ensemble models developed through both the conventional and combined approaches. These statistical metrics are widely accepted for evaluating the accuracy of hydrological models [40]. The expressions were as follows:

$$R^2 = \frac{\left[ \sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y}) \right]^2}{\sum_{i=1}^n (X_i - \bar{X})^2 \sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (1)$$

$$NSE = 1 - \frac{\sum_{i=1}^n (X_i - Y_i)^2}{\sum_{i=1}^n (X_i - \bar{X})^2} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_i - Y_i)^2}{n}} \quad (3)$$

$$MAE = \frac{\sum_{i=1}^n |X_i - Y_i|}{n} \quad (4)$$

where  $n$  is the number of data samples in the time series.  $X_i$  and  $Y_i$  are the  $i$ th observed and predicted dam inflow values, and  $\bar{X}$  and  $\bar{Y}$  are the averages of  $X_i$  and  $Y_i$ , respectively.

$R^2$  measures the strength of the linear relationship between observed and predicted values. It ranges from 0 to 1, a value of 1 indicates a perfect positive correlation.  $NSE$  is a normalized metric that measures the relative magnitude of the residual variance compared to the variance of the observations [41].  $NSE$  values range from  $-\infty$  to 1, with a value of 1 being optimal. The  $RMSE$  and  $MAE$  are commonly used to measure the prediction errors of regression ML models. These metrics can be used together to determine the variation of the errors in a set of model predictions. The  $RMSE$  is always larger than or equal to the  $MAE$ , and the greater the difference between them, the greater the variance in individual

errors in the sample [42]. The values of both metrics range from 0 to  $\infty$ , with values closer to 0 indicating better predictive performance.

### 3. Results and Discussion

#### 3.1. Ensemble Modeling with Conventional and Combined Approaches for Inflow Prediction

Table 2 presents the results of the ensemble models constructed with conventional and combined approaches in AS. In Table 2, the weight indicates the importance of each model in the ensemble. The conventional approach comprised three models: multilayer perceptron (MLP), automatic relevance determination (ARD) regression, and gradient boosting (GB). The results showed that even when the same type of models are included in the ensemble configuration, their weights can be assigned differently based on data and feature preprocessing methods, as well as hyperparameters.

**Table 2.** Ensemble results of AS using conventional and combined approaches.

Model	Dataset	Weight	Data Preprocessing Method	Feature Preprocessing Method	Hyperparameters	Model Type
Conventional model	All data	0.20	encoding = 'one_hot_encoding', imputation = 'mean', rescaling = 'standardize'	extra_trees_preproc_for_regression	activation = 'relu', alpha = $6.03 \times 10^{-7}$ , early_stop = 'valid', hidden_layer_depth = 3, learning_rate_init = 0.0001, n_iter_no_change = 32, num_nodes_per_layer = 100, solver = 'adam'	MLP
		0.04	encoding = 'one_hot_encoding', imputation = 'median', rescaling = 'minmax'	polynomial	activation = 'relu', alpha = $6.11 \times 10^{-5}$ , early_stop = 'valid', hidden_layer_depth = 3, learning_rate_init = 0.0002, n_iter_no_change = 32, num_nodes_per_layer = 101, solver = 'adam'	MLP
		0.38	imputation = 'mean'	polynomial	alpha_1 = $4.70 \times 10^{-5}$ , alpha_2 = 0.0006, lambda_1 = $7.58 \times 10^{-10}$ , lambda_2 = $3.92 \times 10^{-8}$ , threshold_lambda = 4052	ARD regression
		0.26	encoding = 'one_hot_encoding', imputation = 'median', rescaling = 'standardize'	polynomial	max_depth = 'none', max_leaf_nodes = 28, min_samples_leaf = 6, n_iter_no_change = 5, learning_rate = 0.1329, l2_regularization = $8.22 \times 10^{-10}$ , early_stop = 'valid'	GB
		0.04	encoding = 'one_hot_encoding', imputation = 'mean'	polynomial	max_depth = 'none', max_leaf_nodes = 31, min_samples_leaf = 25, n_iter_no_change = 7, learning_rate = 0.1239, l2_regularization = $6.08 \times 10^{-10}$ , early_stop = 'train'	GB
		0.08	encoding = 'one_hot_encoding', imputation = 'median', rescaling = 'minmax'	polynomial	max_depth = 'none', max_leaf_nodes = 26, min_samples_leaf = 6, n_iter_no_change = 20, validation_fraction = 0.08, learning_rate = 0.1530, l2_regularization = 0.013, early_stop = 'valid'	GB
MPE model	High-inflow	0.46	imputation = 'most_frequent', rescaling = 'minmax'	polynomial	max_depth = 'none', max_features = 0.979, max_leaf_nodes = 'none', min_samples_leaf = 1, min_samples_split = 4	Extra-trees
		0.40	encoding = 'one_hot_encoding', imputation = 'mean', rescaling = 'standardize'	extra_trees_preproc_for_regression	activation = 'relu', alpha = $6.03 \times 10^{-7}$ , early_stop = 'valid', hidden_layer_depth = 3, learning_rate_init = 0.0001, n_iter_no_change = 32, num_nodes_per_layer = 100, solver = 'adam'	MLP
		0.10	encoding = 'one_hot_encoding', imputation = 'mean', rescaling = 'minmax'	fast_ica	kernel = 'rbf', degree = 3, gamma = 0.201, tol = 0.021, C = 194.03, epsilon = 0.001, max_iter = -1	SVR
		0.04	encoding = 'one_hot_encoding', imputation = 'most_frequent', rescaling = 'robust_scaler'	select_rates_regression	n_iter = 300, tol = 0.0007, alpha_1 = $2.76 \times 10^{-5}$ , alpha_2 = $9.50 \times 10^{-7}$ , lambda_1 = $6.51 \times 10^{-9}$ , lambda_2 = $4.24 \times 10^{-7}$ , threshold_lambda = 78,251.5, fit_intercept = 'ture'	ARD regression

Table 2. Cont.

Model	Dataset	Weight	Data Preprocessing Method	Feature Preprocessing Method	Hyperparameters	Model Type
	Low-inflow	0.76	imputation = 'most_frequent', rescaling = 'minmax'	fast_ica	kernel = 'rbf', degree = 2, gamma = 0.032, tol = 0.0034, C = 7277.3, epsilon = 0.001, max_iter = -1	SVR
		0.06	encoding = 'one_hot_encoding', imputation = 'median', rescaling = 'minmax'	polynomial	activation = 'relu', alpha = $6.11 \times 10^{-5}$ , early_stop = 'valid', hidden_layer_depth = 3, learning_rate_init = 0.0003, n_iter_no_change = 32, num_nodes_per_layer = 101, solver = 'adam'	MLP
		0.06	imputation = 'mean'	polynomial	n_iter= 300, tol = 0.0091, alpha_1 = $4.70 \times 10^{-5}$ , alpha_2 = 0.0006, lambda_1 = $7.58 \times 10^{-10}$ , lambda_2 = $3.92 \times 10^{-8}$ , threshold_lambda = 4052, fit_intercept = 'ture'	ARD regression
		0.04	imputation = 'mean', rescaling = 'power_transformer'	euclidean	n_estimator = 140, learning_rate = 0.2841, loss = 'exponential', max_depth = 8	Adaboost
		0.08	encoding = 'one_hot_encoding', imputation = 'mean', rescaling = 'standardize'	no_preprocessing	max_depth = 'none', max_leaf_nodes = 9, min_samples_leaf = 2, n_iter_no_change = 20, learning_rate = 0.0913, l2_regularization = 0.0057, early_stop = 'train'	GB

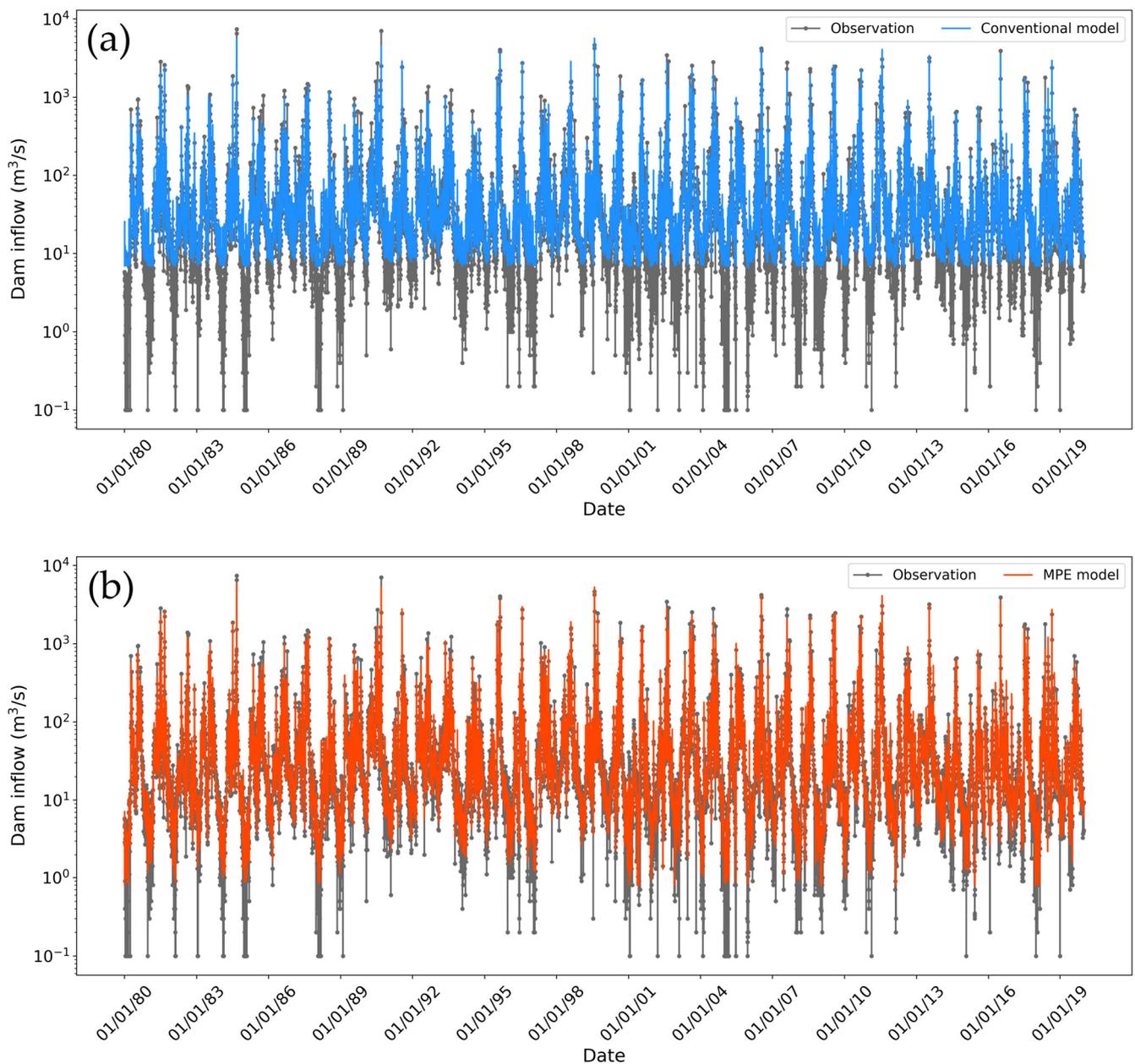
The ensemble model for high-inflow prediction consisted of extremely randomized trees (extra-trees), MLP, support vector regression (SVR), and ARD regression models. The extra-trees and MLP models had a significant impact, with weights of 0.46 and 0.40, respectively, demonstrating the models' effectiveness in the training data and their significant contribution to accurate predictions. As a tree-based ensemble model, extra-trees builds multiple decision trees on randomly sampled subsets of data, displaying a high proficiency for capturing complex relationships. It is recognized for its reduction in variance and bias, as well as its computational efficiency and ability to handle noisy and nonlinear data [43]. The MLP can solve complex nonlinear relationships and is commonly used for high-dimensional problems. As demonstrated by Hong et al. [30], the MLP predicts high inflow more accurately than other models, such as the random forest and GB models. These results indicate that the high-inflow prediction ensemble model can effectively handle the complex and high-dimensional data structure, resulting in accurate predictions. In contrast, the low-inflow prediction ensemble model consisted of five models, with the SVR having the highest weight of 0.76. This highlights the effectiveness of SVR in accurately predicting low inflow compared to other models. The SVR has been widely and successfully applied in several studies for river flow prediction [44–46]. Furthermore, research conducted by Adamowski [47] and Yuan and Forshay [48] found that the SVR effectively captures nonlinear features of low flow, such as baseflow and groundwater. Sahoo et al. [49] also demonstrated the satisfactory performance of SVR in predicting monthly low flow for the Mahanadi river basin.

The study results confirmed the effectiveness of using separate training datasets for high inflow and low inflow in achieving a suitable ensemble configuration that reflects the unique characteristics of each dataset. In this study, the `time_left_for_this_task` and `per_run_time_limit` parameters, which determine the time budget in meta-learning for developing high-inflow and low-inflow prediction ensemble models, were set to the same value. The time budget in AS refers to the maximum time allowed for fitting and evaluating ML models for a specific dataset and may vary based on the dataset's characteristics [50]. The time budget parameters can be adjusted by the user according to the size and complexity of the dataset, and available computational resources. Determining an optimal time budget that considers the characteristics of different datasets will be necessary for generating accurate and efficient ensemble results in the future. Furthermore, understanding the contribution of each model to the final prediction can be difficult, which may limit the interpretability of the AS-based ensemble model. Therefore, future research should evaluate the applicability of various analysis techniques such as SHAP (SHapley Additive

exPlanations) [51] and LIME (Local Interpretable Model-Agnostic Explanations) [52] to increase the interpretability of the ensemble model.

### 3.2. Comparison of Dam Inflow Prediction Performance

Figure 6 compares the time series of the predicted dam inflow with the observed values for the conventional and MPE models during the training and testing periods. Both models showed a reasonable prediction performance similar to previous studies [30,31,33] on dam inflow prediction using ML and deep learning (Table 3). However, the conventional model had limitations in predicting low inflow below  $10 \text{ m}^3/\text{s}$  compared to the MPE model. This suggests that conventional AS-based ensemble models trained on the entire dataset may have been underfitted, resulting in an inaccurate capture of the characteristics of low-inflow data.

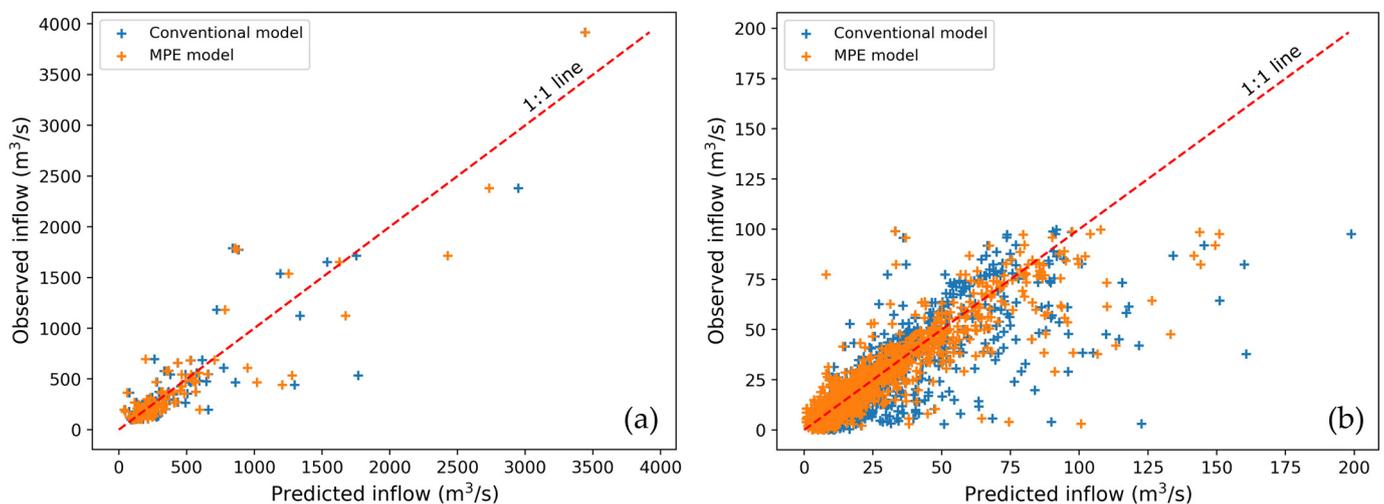


**Figure 6.** Comparison of predicted and observed inflow using both models with training (a) and test (b) data.

**Table 3.** Comparison of performance of both models on training and test data.

Model	Training Period (1985–2015)				Test Period (2016–2019)			
	$R^2$	$NSE$	$RMSE$	$MAE$	$R^2$	$NSE$	$RMSE$	$MAE$
Conventional model	0.91	0.90	70.74	19.51	0.86	0.85	67.18	17.21
MPE model	0.95	0.94	55.48	14.01	0.88	0.87	63.93	15.29

Figure 7b shows that the MPE model outperforms the conventional model for low-inflow values ( $<100 \text{ m}^3/\text{s}$ ), while there is no significant difference between the models for high-inflow data (Figure 7a). Table 4 summarizes the performance of the two AS-based ensemble models for each test dataset. The MPE model improves  $RMSE$  and  $MAE$  by 4.2% and 1.6%, respectively, and increases  $R^2$  and  $NSE$  by 2.5% and 35.8%, respectively, for low-inflow data. For high-inflow data, it reduces  $RMSE$  and  $MAE$  by 22.1% and 24.9%, respectively, and increases  $R^2$  and  $NSE$  by 21.9% and 35.8%, respectively.

**Figure 7.** Scatter plots of predictions of both models using separate test data for (a)  $\geq 100 \text{ m}^3/\text{s}$  and (b)  $< 100 \text{ m}^3/\text{s}$ .**Table 4.** Comparison of performance of both models on separate test data.

Period	Model	Inflow Condition	$R^2$	$NSE$	$RMSE$	$MAE$
Training	Conventional model	$\geq 100 \text{ m}^3/\text{s}$	0.89	0.88	190.21	89.99
		$< 100 \text{ m}^3/\text{s}$	0.62	0.48	16.26	8.79
	MPE model	$\geq 100 \text{ m}^3/\text{s}$	0.93	0.93	149.76	65.65
		$< 100 \text{ m}^3/\text{s}$	0.79	0.73	11.69	6.15
Testing	Conventional model	$\geq 100 \text{ m}^3/\text{s}$	0.80	0.80	210.76	103.13
		$< 100 \text{ m}^3/\text{s}$	0.64	0.53	13.91	7.92
	MPE model	$\geq 100 \text{ m}^3/\text{s}$	0.82	0.82	201.91	101.50
		$< 100 \text{ m}^3/\text{s}$	0.78	0.72	10.84	5.95

This improved performance can be attributed to the MPE model's combined approach, where models are trained separately for high-inflow and low-inflow datasets, allowing for the optimization of the models using the Bayesian optimization algorithm in AS. In contrast, conventional model approaches trained on the entire dataset are less likely to be optimized for each flow regime, leading to poor predictive ability and low-flow regimes.

This highlights the importance of optimizing models for different flow regimes, especially low-flow regimes, to improve their predictive ability.

It is noteworthy that the prediction performance of the AS-based ensemble models for dam inflow does not show a significant difference compared to other standalone and combined ML models. The performance of an ML model for a specific dataset can also be improved by the efforts of experts, rather than relying on meta-learning-based AS [53]. This means that AS cannot guarantee the development of the optimal prediction model for a given dataset. Furthermore, Tanaka et al. [54] found that the accuracy of an AS-based ensemble model in predicting the number of defects in software modules was comparable to that of an RF model. Shi et al. [53] also showed that the AS-based ensemble model had high performance in predicting concrete compressive strength, but there was no significant difference between its performance and that of an independent model built by an expert. However, their studies commonly demonstrated that even without extensive knowledge of ML, AS can still be utilized to construct a robust ensemble model with satisfactory predictive performance.

The development of a robust ensemble model is time- and labor-intensive and can be difficult for nonexperts. From these perspectives, AS is considered useful in efficiently developing robust ensemble models objectively and rationally, minimizing user subjectivity, and without manual processes such as preprocessing, hyperparameter optimization, and model combination. The ensemble model, based on the combined approach in this study is expected to improve the model prediction's accuracy by resolving the imbalance of the given dataset.

### 3.3. Comparison of AS-Based Ensemble Models for Dam Inflow Prediction Using FDC Analysis

The flow duration curve (FDC) is a cumulative frequency plot that displays the percentage of time-specified discharges that were equaled or exceeded during a given period [55]. The FDC is generally divided into five zones, representing different hydrologic conditions of a stream: high flow (0–10%), moist conditions (10–40%), mid-range flow (40–60%), dry conditions (60–90%), and low flow (90–100%). This can help identify sustainable water resource management plans. In this study, AS-based ensemble models were developed using conventional and combined approaches to predict dam inflow, and their performance was evaluated using FDC.

Figure 8 shows the FDCs for the dam inflow test dataset predicted by the MPE and conventional models. The AS-based ensemble models had good agreement with the observed values (<40% exceedance probability), while the conventional model performed poorly towards the lower portion of FDCs. As shown in Table 5, the MPE model performed better for the intervals below the mid-range flow range and yielded low-inflow data more accurately than the conventional model for all seasons (Figure 9). These results suggest that, although both ensemble models predicted the high inflow in the flood period with satisfactory performance, the combined approach is needed to capture the low-inflow behavior in the nonflood period well.

**Table 5.** Comparison of performance of both models for flow regimes.

Model	Metric	High Flow	Moist Conditions	Mid-Range Flow	Dry Conditions	Low Flow
Conventional model	$R^2$	0.97	0.99	0.99	0.97	0.97
	$NSE$	0.97	0.97	0.76	−0.43	−19.90
	$RMSE$	78.67	2.93	1.50	2.93	5.40
	$MAE$	28.08	2.14	1.41	2.77	5.37
MPE model	$R^2$	0.96	1.00	0.99	0.98	0.97
	$NSE$	0.96	0.97	0.95	0.95	0.41
	$RMSE$	90.96	3.04	0.68	0.52	0.91
	$MAE$	34.53	2.13	0.56	0.42	0.88

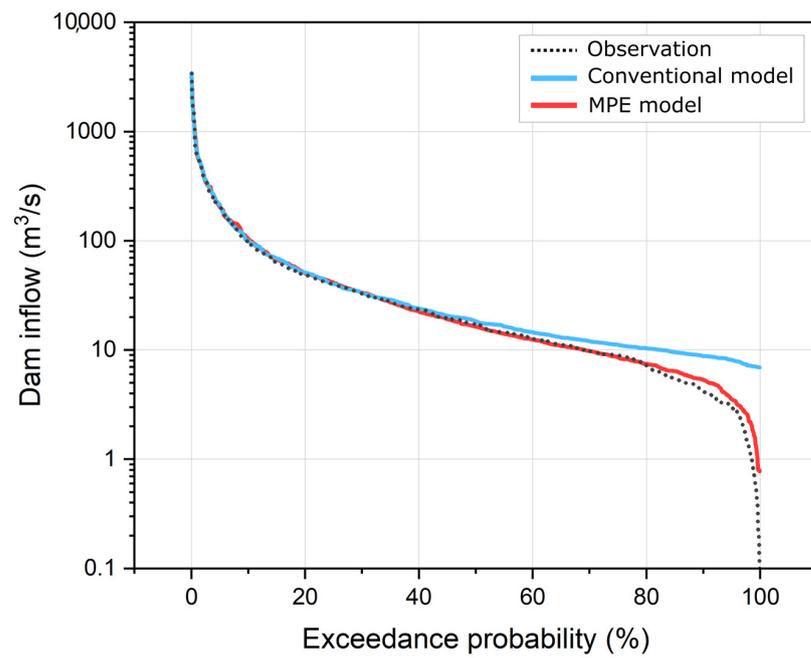


Figure 8. FDCs of observed inflow and inflow predicted by both models during the whole test period.

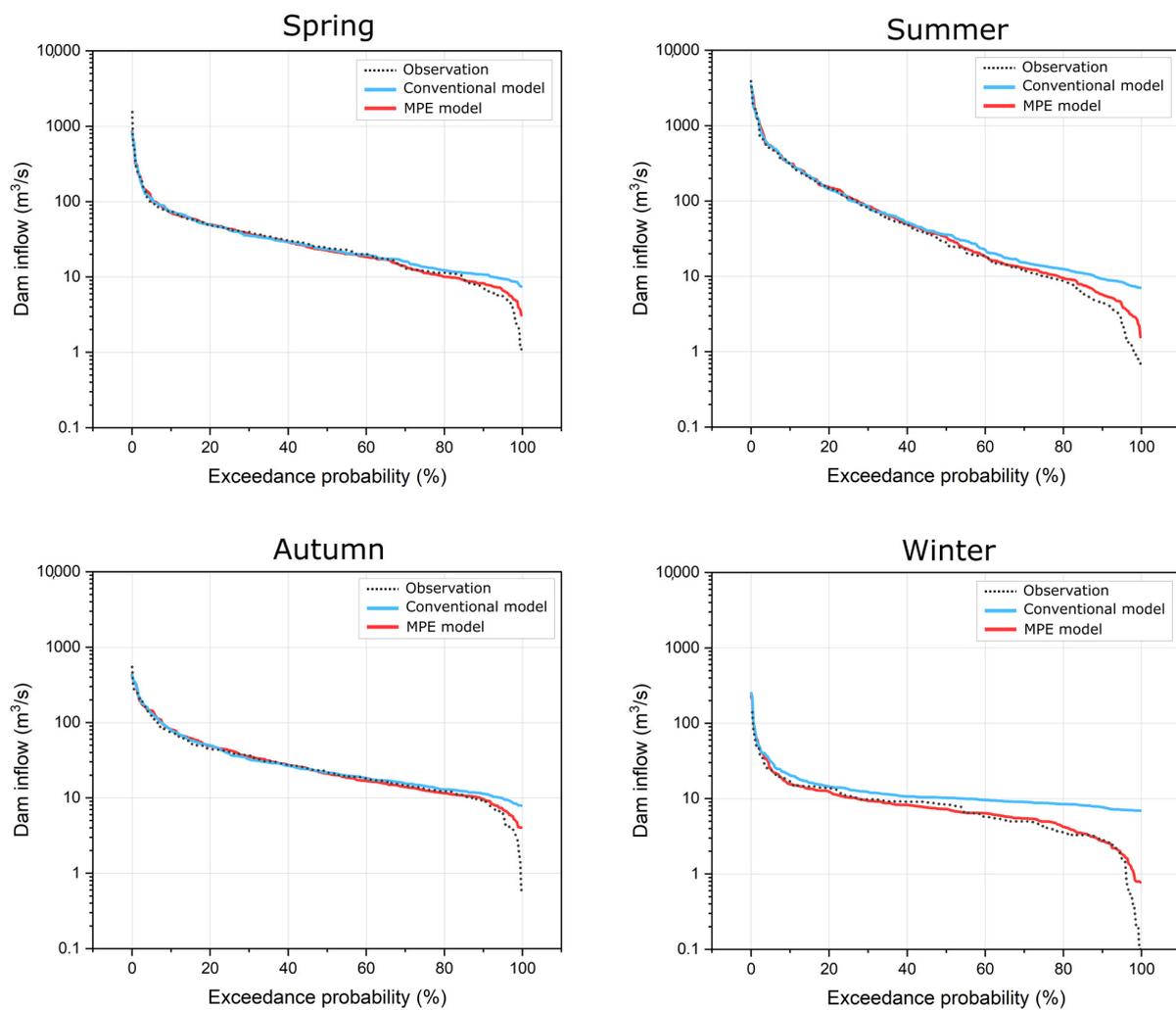


Figure 9. FDCs of predicted and observed seasonal inflows.

More specifically, Figure 10 compares the observed and predicted low inflow values using the models for each season (>60% exceedance probability), showing that the MPE model had higher  $R^2$  and  $NSE$  than the conventional model, reducing  $RMSE$  and  $MAE$  by 58.8–88.5% and 54.1–89.9%, respectively (Table 6). This indicates that the integration of ensemble models for high and low flows is necessary to produce accurate dam inflow prediction data that takes into account the seasonal characteristics of floods and dry periods. Through the above results, we confirm that the MPE model is suitable for generating seasonal low-inflow data for decision-making in dam operation, especially in the SRD basin, where 61% (756.7 mm) of rainfall occurs from June to August due to the Asian monsoon. The water level of a dam can be affected by various factors, including evapotranspiration, topography, and groundwater; however, it is directly affected by the inflow from the watershed upstream of the dam [56]. Climate change may cause changes in streamflow regimes, leading to flow variability and extreme seasonality [57,58]. Hence, the MPE model can provide accurate and consistent dam inflow prediction results for both flood and nonflood seasons, allowing for appropriate hydrological manipulations to ensure water storage and prepare for potential flood damage in downstream regions.

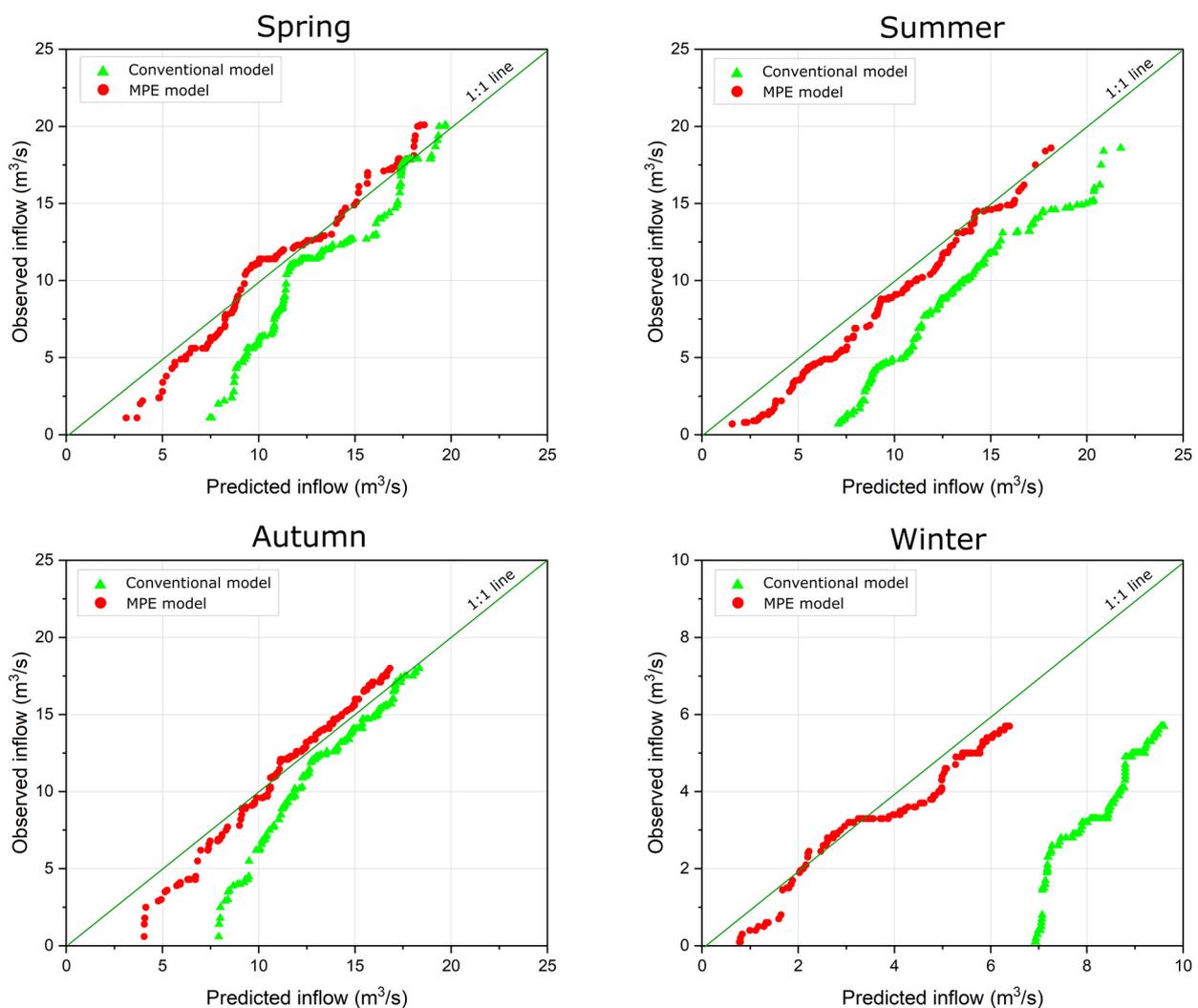


Figure 10. Scatter plots of predictions of both models for seasonal low inflows.

**Table 6.** Comparison of performance of both models for seasonal low inflows.

Model	Metric	Spring (Mar–May)	Summer (Jun–Aug)	Autumn (Sep–Nov)	Winter (Dec–Feb)
Conventional model	$R^2$	0.95	0.97	0.97	0.93
	$NSE$	0.65	0.03	0.68	−9.20
	$RMSE$	2.76	4.54	2.38	4.80
	$MAE$	2.24	4.43	1.81	4.74
MPE model	$R^2$	0.97	0.99	0.99	0.96
	$NSE$	0.95	0.93	0.95	0.86
	$RMSE$	1.02	1.26	0.98	0.55
	$MAE$	0.85	1.16	0.83	0.48

#### 4. Conclusions

In this study, we aimed to develop a robust and efficient AS-based ensemble model for predicting multi-inflow in dam reservoirs. Our approach involved the development of the MPE model, which combined two types of datasets for high and low inflow conditions to predict multi-inflow. Our results show that the MPE model outperforms a conventional model in predicting both high and low inflow conditions, demonstrating the effectiveness of our ensemble approach in addressing the imbalance between high and low inflow observations in the dataset. Additionally, the MPE model was found to capture the characteristics of each flow regime and make more accurate predictions for each condition.

Our study contributes to the field of water resource management by providing a reliable method for predicting dam inflow that can inform better decision-making and planning for flood and nonflood periods. Our findings highlight the importance of using an ensemble approach to overcome the challenges associated with predicting multi-inflow and suggest that the AS-based ensemble model can be used as a tool by nonexperts without domain knowledge related to ML.

Although our study presents promising results, it is not without limitations. For instance, the study only used data from a single dam reservoir and may not generalize to other regions with different hydrological conditions. Furthermore, although we demonstrated the effectiveness of our ensemble approach, more research is needed to evaluate the robustness of the model in the face of uncertainty and other potential factors that may affect its predictive performance.

Future research could explore the potential impact of model uncertainty analysis on the predictive performance of the MPE model and its ability to make reliable predictions for various inflow conditions. Additionally, improving the library for AS to generate integrated prediction results using various ensemble models trained according to data standards set by the user could eliminate the need for manual separation of datasets and enable nonexperts to use AS-based ensemble model development.

Overall, our study underscores the scientific value added to the field of water resource management by providing a reliable method for predicting dam inflow using an ensemble approach. Our results have important implications for policymakers and decision-makers, highlighting the need to invest in the development of robust and efficient AS-based ensemble models for predicting multi-inflow in dam reservoirs.

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