

Article

A Physics-Inspired Stochastic Resonance Framework for Enhancing Machine Learning Streamflow Forecasting

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Abstract

Climate change introduces severe non-stationarity and high-frequency noise into hydro-meteorological data. This noise degrades the predictive accuracy of traditional data-driven streamflow models. We propose a physics-inspired data enhancement framework coupling the CEEMDAN-based Hilbert-Huang Transform (HHT) with Stochastic Resonance (SR). We applied this framework to the Lanzhou section of the upper Yellow River. HHT isolates the dominant characteristic frequency of the basin's streamflow system at 0.0026 cycles/day. Using this frequency as a target, we constructed a Bayesian-optimized SR system. The system converts the energy of high-frequency meteorological noise into low-frequency periodic components, facilitating frequency alignment between the meteorological inputs and the hydrological response. We evaluated the SR-enhanced meteorological inputs across three machine learning architectures: Random Forest, XGBoost, and LSTM. All algorithms demonstrated an improved performance. The SR-LSTM model achieved a Nash-Sutcliffe Efficiency (NSE) of 0.91 ± 0.03 . This represents a 19% improvement over the baseline LSTM score of 0.79 ± 0.02 . The SR-LSTM demonstrated robust accuracy during extreme hydrological events; it achieved a high-flow NSE of 0.89 and effectively mitigated the common peak-underestimation issue by constraining relative peak magnitude errors to approximately -5.08%. Overall, this study presents a practical data enhancement approach for streamflow forecasting under complex climatic conditions.

Keywords: stochastic resonance; Physics-Inspired Machine Learning; Hilbert-Huang Transform; streamflow forecasting; Multi-model learning

Academic Editor: Bommanna
Krishnappan

Received: 14 May 2026
Revised: 25 June 2026
Accepted: 26 June 2026
Published: 29 June 2026

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1. Introduction

Streamflow forecasting provides the foundation for basin-scale water resource management, flood mitigation, and ecological conservation [1–3]. However, climate change has intensified the hydrological cycle, increasing the spatiotemporal heterogeneity of precipitation and evaporation [4]. This amplification introduces severe non-stationarity and high-frequency noise into basin hydrological processes [5–8]. The Lanzhou section of the upper Yellow River basin, a climate-sensitive, semi-arid region, exemplifies these conditions, experiencing a clear warming and drying regime shift over the past two decades [9–11]. These abrupt environmental fluctuations render the rainfall-streamflow relation-

ship highly non-linear and obscured by stochastic noise. Consequently, traditional hydrological forecasting models relying on stationary assumptions face significant performance degradation, frequently failing to capture complex streamflow variability during extreme hydrological events [12–15].

Data-driven algorithms, particularly Machine Learning (ML) and Deep Learning (DL), have become prominent in hydrological forecasting due to their robust non-linear mapping capabilities [16–18]. Nevertheless, their predictive efficacy is strictly bounded by input data quality. Prevalent pre-processing strategies typically address non-stationarity via time-frequency decomposition of the target streamflow series, utilizing techniques like the Wavelet Transform (WT) and Empirical Mode Decomposition (EMD) to reduce modeling complexity [16,19–21]. However, this output-centric approach overlooks a critical limitation: the meteorological forcing data (e.g., precipitation, evapotranspiration) serving as system inputs are also heavily obscured by high-frequency stochastic noise [22,23]. Feeding raw, noisy data directly into neural networks conceals the true climatic driving mechanisms. It also forces algorithms to overfit transient perturbations during training [24]. Ultimately, this compromises the models' generalization capacity and physical interpretability in dynamically changing environments [25,26].

Moving from noise elimination to noise utilization offers a practical solution for environments with low signal-to-noise ratios. Stochastic Resonance (SR) provides a promising alternative perspective for tackling this issue [27,28]. SR differs from traditional destructive filtering. It describes a dynamic in nonlinear systems in which an optimal level of broadband noise synergizes with a weak periodic signal. Bistable transitions mathematically transfer the energy of high-frequency noise to the low-frequency characteristic signal. This transfer directly amplifies the Signal-to-Noise Ratio (SNR) [29]. Researchers have successfully applied SR theory in mechanical fault diagnosis and biological neural coding [30–32]. Its application in hydro-meteorological data enhancement remains largely unexplored. We hypothesize that the Hilbert-Huang Transform (HHT) can isolate the characteristic frequency of a basin's hydrological response [33]. Establishing this frequency as a physical target for the SR system induces resonance between the noisy meteorological inputs and the streamflow response. This physics-inspired strategy does more than smooth data. It actively reconstructs meteorological driving patterns synchronized with the basin's natural pulse. This reconstruction generates physics-inspired inputs for downstream machine learning models.

To address the critical bottleneck of low signal-to-noise ratios in hydro-meteorological forecasting, this study shifts the paradigm from traditional noise elimination to active noise utilization. We propose a physics-inspired data enhancement framework that couples the Hilbert-Huang Transform (HHT) with Stochastic Resonance (SR). Applied to the climate-sensitive Lanzhou section of the upper Yellow River (2007–2024), this framework aims to reconstruct meteorological input patterns synchronized with the basin's natural hydrological rhythm. The main contributions of this study are summarized as follows: (i) We introduce a model-agnostic SR mechanism guided by HHT. (ii) By decomposing historical streamflow series, we quantitatively extracted the dominant characteristic frequency of the basin, utilizing it as a target frequency to facilitate input-output frequency alignment in the SR system. (iii) Through feature importance analysis, we provide quantitative evidence that the proposed framework enhances the representational robustness of the model, shifting its predictive reliance from simple autoregressive extrapolation toward more informative, SR-enhanced meteorological predictors.

2. Materials and Methods

2.1. Study Area and Data

We evaluated the framework using data from the Lanzhou section of the upper Yellow River basin (36°03' N, 103°40' E). This catchment sits at the climatic ecotone between the Qinghai–Tibet Plateau and the Loess Plateau, marking a complex transition from semi-arid to semi-humid conditions (Figure 1). Mean annual precipitation is sparse (300 to 500 mm) and highly heterogeneous. Annual potential evapotranspiration (PET) consistently exceeds 1500 mm. Global climate change amplifies seasonal and interannual fluctuations in meteorological forcing factors. These climatic shifts generate characteristically flashy streamflow hydrographs with steeply rising and rapidly receding limbs. The resulting environmental dynamics create a highly non-stationary and non-linear hydroclimatic system. Meteorological time series in this region contain heavy stochastic noise. This region, therefore, presents a challenging scenario for evaluation. It exposes the predictive limits of data-driven models and tests the efficacy of physics-inspired enhancement algorithms.

This study uses an 18-year daily hydro-meteorological dataset (1 January 2007, to 31 December 2024). We acquired daily streamflow data (Flow) from the Hydrological Yearbook published by the Yellow River Conservancy Commission (YRCC). The China Meteorological Data Service Centre (CMDC) supplied the daily meteorological forcing data from national ground-based stations. This meteorological dataset includes precipitation (PRE), mean air temperature (TEM), relative humidity (RHU), and wind speed (Wind). We applied the Thiessen polygon spatial interpolation method to generate basin-averaged meteorological series. The FAO Penman-Monteith equation is used to calculate potential evapotranspiration (PET). Deep learning models require continuous sequential data for training. We applied linear interpolation to fill missing values, which accounted for less than 1% of the total records. To prevent data leakage, we partitioned the dataset chronologically into training, validation, and testing sets with a ratio of 7:1:2. The data normalization process was also carefully designed to avoid data leakage: normalization parameters (e.g., mean and standard deviation) were calculated exclusively from the training set and subsequently applied to scale the validation and testing sets. Furthermore, only the training subset was input into the HHT-SR system; the subsequent data enhancement was performed based entirely on the characteristic frequencies and optimized parameters derived from the training set. Data leakage was prevented throughout the entire experimental process.

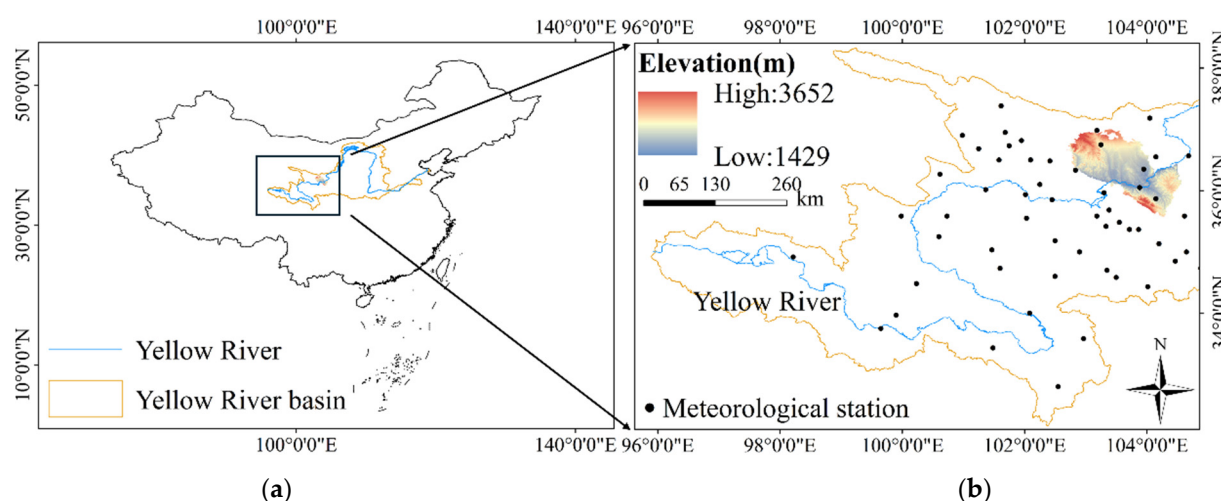


Figure 1. Geographical location and topographic features of the study area. (a) Map of China showing the Yellow River (blue line) and the Yellow River Basin (orange outline), with the black box indicating the specific research region situated in the upper reaches. (b) Detailed Digital Elevation

Model (DEM) of the Lanzhou section of the Yellow River. The color gradient from blue to red represents the elevation distribution, ranging from 1429 m to 3652 m. The significant elevation difference and complex terrain characteristics play a crucial role in the hydrological response and streamflow generation.

2.2. Methodology

The workflow integrates three core modules (Figure 2): (i) Feature Identification: A CEEMDAN-based Hilbert-Huang Transform (HHT) framework is applied strictly to the training streamflow series to extract the system's variance-dominant characteristic frequency. To address mode-mixing and ensure the decomposition's robustness against noise, this study utilized the Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) algorithm, implemented via the PyEMD package. The ensemble size was set to 100 trials, with an added noise standard deviation of 0.05. During the sifting process, cubic spline interpolation was used for envelope fitting, and extrema mirroring was applied to mitigate endpoint effects. The stopping criterion was managed by the standard Cauchy-type convergence threshold. To compute the representative frequency from the instantaneous frequencies derived via the Hilbert transform, an energy-weighted averaging method was applied using squared amplitudes as weights. Non-physical frequency anomalies were filtered out by restricting the valid frequency range to $0 < f < 0.5$ cycles/day. (ii) Physics-Inspired Enhancement: This characteristic frequency, isolated from the training data, serves as the target for the Stochastic Resonance (SR) system. The Bayesian Optimization Algorithm (BOA) is employed strictly within the training phase to optimize the system dynamics equations, maximizing the Signal-to-Noise Ratio (SNR) to generate enhanced meteorological driving data. (iii) Prediction and Evaluation: The normalized, enhanced data are fed into machine learning models (e.g., RF, XGBoost, LSTM), followed by a comprehensive performance assessment using multiple statistical metrics.

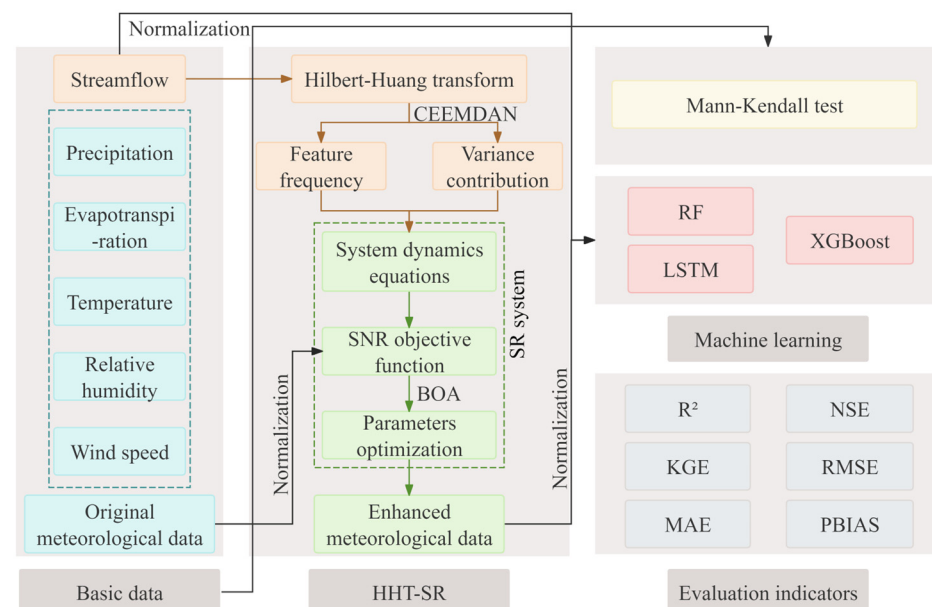


Figure 2. Schematic diagram of the proposed HHT-SR-ML coupling framework for streamflow forecasting.

Background noise complicates predictive modeling of hydro-meteorological systems. It frequently obscures weak periodic signals. We address this by coupling the Hilbert-Huang Transform (HHT) with Adaptive Stochastic Resonance (SR). HHT first isolates the

Feature Frequency (FF) from the historical streamflow data. We then use this FF to guide the SR system. The SR system actively transfers energy from stochastic noise into the valid periodic components of the meteorological drivers. This directed energy transfer maximizes the input signal-to-noise ratio (SNR). Given that the hydro-meteorological dataset is on a daily temporal scale, the sampling frequency of our system is defined as $f_s = 1 \text{ d}^{-1}$. Consequently, the frequencies extracted via HHT and utilized in the SR optimization are normalized discrete frequencies, with units of cycles per day (d^{-1}) rather than Hertz (Hz).

2.2.1. Mathematical Characterization of Bistable SR Dynamics

Stochastic Resonance (SR) amplifies weak signals by combining a nonlinear system, an external driving signal, and background noise. We model the meteorological variables as Brownian particles moving through a potential field. The Langevin equation governs their dynamic behavior:

$$\frac{dx}{dt} = -\frac{dV(x)}{dx} + S(t) + N(t) \quad (1)$$

where x represents the system's output state, and $V(x)$ is the potential function. The input signal, $S(t)$, contains the periodic features. $N(t)$ represents Gaussian white noise. We apply the classical bistable potential function to drive the energy transfer within the complex hydrological system. It is defined as:

$$V(x) = -\frac{a}{2}x^2 + \frac{b}{4}x^4 \quad (2)$$

By substituting this potential function into the governing dynamic equation, the evolution equation of the bistable SR system is derived as follows:

$$\frac{dx}{dt} = ax - bx^3 + S(t) + N(t) \quad (3)$$

where the parameters a and b define the system's structural geometry. They establish the potential barrier height as $\Delta V = a^2/4b$. The input signal and background noise combine to generate energy. Once this combined energy exceeds the barrier threshold (ΔV), the particle transitions periodically between the two stable states. This inter-well hopping creates a stochastic synchronization that directly amplifies the target signal.

The nonlinear stochastic differential equation lacks a closed-form analytical solution. We apply the fourth-order Runge–Kutta (RK4) algorithm for numerical integration. After standardizing the input sequence and setting a discretization step size (h), we establish the following iterative numerical scheme:

$$k_1 = h \left[ax_t - bx_t^3 + \eta_t \right] \quad (4)$$

$$k_2 = h \left[a \left(x_t + \frac{k_1}{2} \right) - b \left(x_t + \frac{k_1}{2} \right)^3 + \eta_t \right] \quad (5)$$

$$k_3 = h \left[a \left(x_t + \frac{k_2}{2} \right) - b \left(x_t + \frac{k_2}{2} \right)^3 + \eta_t \right] \quad (6)$$

$$k_4 = h \left[a \left(x_t + k_3 \right) - b \left(x_t + k_3 \right)^3 + \eta_t \right] \quad (7)$$

$$x_{t+1} = x_t + \frac{1}{6} (k_1 + 2k_2 + 2k_3 + k_4) \quad (8)$$

where η_t corresponds to the noise-embedded input data that has undergone standardization processing.

2.2.2. Feature Frequency Extraction via Hilbert-Huang Transform (HHT)

The Stochastic Resonance (SR) system depends on matching its parameters to the input signal's frequency. Periodic behaviors in hydrological time series, however, often remain hidden. We apply the Hilbert-Huang Transform (HHT) to historical streamflow data to extract these underlying feature frequencies.

The process begins with Empirical Mode Decomposition (EMD). EMD decomposes the non-stationary streamflow series, $x(t)$, into a finite set of Intrinsic Mode Functions (IMFs) and a residual trend. We use an iterative sifting process until the extracted components meet the strict definition of an IMF. The reconstructed signal is then expressed as:

$$x(t) = \sum_{i=1}^{k-1} c_i(t) + r_k(t) \quad (9)$$

In this expression, $c_i(t)$ represents the i order IMF component, while $r_k(t)$ denotes the monotonic trend term. To quantitatively assess the relative dominance of each component within the original series, the Variance Contribution Rate (MCR) is calculated as follows:

$$E_i = \frac{1}{n} \sum_{t=1}^n \left[c_i(t) - \frac{1}{n} \sum_{t=1}^n c_i(t) \right]^2 \quad (10)$$

$$M_i = \frac{E_i}{\sum_{i=1}^{k-1} E_i + \text{var}[r_k(t)]} \quad (11)$$

Subsequently, the Hilbert Transform (HT) is applied to the dominant IMF components (those exhibiting significant MCR values) to derive their analytic signals. The transformation is defined by the Cauchy principal value integral:

$$H_c[c_i(t)] = \frac{1}{\pi} \int_{-\infty}^{\infty} \frac{c_i(\tau)}{t - \tau} d\tau \quad (12)$$

$$\varphi_i(t) = \arctan \frac{H_c[c_i(t)]}{c_i(t)} \quad (13)$$

$$w_i = \frac{1}{n} \sum_{t=1}^n \frac{d\varphi_i(t)}{dt} \quad (14)$$

Ultimately, the instantaneous central frequency, w_i , derived from these analytic signals, is designated as the Feature Frequency (FF) of the hydrological process, serving as the target parameter for the subsequent SR system tuning.

2.2.3. Adaptive Parameter Optimization and Signal Reconstruction

We synchronize the meteorological driving factors and hydrological streamflow processes by setting the extracted streamflow feature frequency as the SR system's target reference. We optimize the structural parameters, a and b , to maximize the SR output's spectral energy density at this specific frequency.

A Weighted Signal-to-Noise Ratio (SNR) serves as the objective function for this optimization. This metric incorporates the identified feature frequency (w_i) and its variance contribution rate (M_i):

$$\text{SNR} = 10 \cdot \lg \frac{\sum_{i=1}^{k-1} M_i \cdot P(w_i - f_w, w_i + f_w)}{P(f) - \sum_{i=1}^{k-1} M_i \cdot P(w_i - f_w, w_i + f_w)} \quad (15)$$

where P represents the power spectral density within a specific frequency band, f_w is the frequency bandwidth, and P_{total} is the total spectral energy. The mapping between the parameter space (a, b) and the output SNR forms a complex, non-convex topology. Traditional gradient-based methods often fail in this space. We apply the Bayesian Optimization Algorithm (BOA) to find the global optimum. BOA uses posterior probability models to evaluate the search space. It efficiently locates the optimal parameter set (a_{opt}, b_{opt}) that maximizes the SNR with minimal iterations.

We incorporate these optimized parameters into the bistable system to process the raw meteorological inputs. This step produces the SR-enhanced meteorological data series. The resulting data features a maximized signal-to-noise ratio and serves as the direct input for the subsequent hydrological simulations.

To ensure full algorithmic transparency and experimental reproducibility, the Stochastic Resonance (SR) signal enhancement process was rigorously parameterized. The bistable potential well parameters, a and b , strictly dictate the system's barrier height and well width. During the optimization process, the search space was bounded to a in $[0.1, 1.5]$ and b in $[0.001, 0.5]$. These constraints were physically motivated to prevent numerical divergence and ensure sufficient well-depth for the signal particle to undergo resonance transitions. The optimization objective was set to maximize the output Signal-to-Noise Ratio (SNR) at the target characteristic frequency. The Bayesian Optimization framework was configured with 5 initial exploration points followed by 15 optimization iterations. Furthermore, to guarantee exact reproducibility across all stochastic processes within the framework, including the 100 noise-added ensemble trials in CEEMDAN (with a noise standard deviation of 0.05) and the Bayesian hyperparameter sampling, a global random seed (`random_state = 42`) was fixed.

2.3. Machine Learning Architectures and Optimization

We sequentially partitioned the datasets chronologically into training (70%), validation (10%), and testing (20%) sets, covering the period from January 2007 to December 2024. This strictly chronological split prevents future data leakage and maintains temporal continuity. To ensure reproducibility across all experiments, a global random seed was fixed at 42. The task was formulated as a single-step-ahead forecasting problem, defining the runoff at the future time step $t + 1$, denoted as $R(t + 1)$, as the target variable. To capture hydrological inertia, all models incorporated a one-step lagged streamflow feature, $R(t)$. For the tree-based models (Random Forest and XGBoost), the future runoff $R(t + 1)$ was predicted using the concurrent meteorological predictors at time t (PET, PRE, RHU, TEM, and Wind) alongside the historical streamflow $R(t)$. For the Long Short-Term Memory (LSTM) model, the input timing was framed as a historical sequence mapping. Specifically, to predict $R(t + 1)$, the LSTM consumed an input matrix spanning from time step $t - T + 1$ to t , where T represents the look-back window length. This temporal alignment ensures that no model has access to the unobserved meteorological conditions of time $t + 1$ during the forecasting phase, ensuring a fair and causal comparison. The input window length T for the LSTM was dynamically optimized within the Bayesian Optimization framework over a range of 5–30 time steps.

We evaluated the enhanced data using three distinct machine learning architectures. All hyperparameters were tuned utilizing a Bayesian Optimization framework driven by the Tree-structured Parzen Estimator (TPE) algorithm, targeting the minimization of the validation Root Mean Square Error (RMSE). To ensure methodological consistency, feature importance was quantified using Permutation Importance calculated exclusively on the testing set. This approach measures the degradation in model performance when a specific feature's values are randomly shuffled, providing a robust, model-agnostic metric to evaluate the contribution of each input variable to the predictive accuracy.

(i) Random Forest (RF): We leveraged RF for its robust ensemble learning capability and its ability to capture nonlinear hydro-climatic relationships while mitigating overfitting through ensemble averaging. The optimization process spanned 50 Bayesian iterations, tuning parameters including the number of trees, maximum tree depth, minimum samples split, minimum samples leaf, and maximum features.

(ii) XGBoost: This gradient boosting framework was employed to decipher complex nonlinear feature interactions through its built-in L1/L2 regularization. The architecture was optimized using the TPE-based framework over 50 iterations, with an early-stopping patience of 50 rounds implemented to strictly prevent overfitting.

(iii) Long Short-Term Memory (LSTM): The LSTM architecture was specifically designed to capture the long-term temporal dependencies in the runoff routing process. The network architecture searched between one and two stacked unidirectional LSTM layers, followed by a fully connected dense layer. The model was trained utilizing the Adam optimizer (PyTorch, version 2.1.0) coupled with a dynamic learning rate scheduler (ReduceLROnPlateau, PyTorch, version 2.1.0). The LSTM hyperparameter search involved 20 Bayesian Optimization iterations. During the final training phase, the model ran for a maximum of 200 epochs with an early-stopping patience of 30 epochs. Crucially, to account for stochastic variance inherent in neural network weight initialization, the LSTM model was evaluated across 30 independent random seed initializations. The mean and standard deviation of the test metrics across these 30 independent runs were reported to ensure high statistical robustness.

The comprehensive hyperparameter search spaces and the final tuned configurations for all three architectures are detailed in Table 1.

Table 1. Hyperparameter search spaces and optimization configurations for RF, XGBoost, and LSTM models.

Model	Hyperparameter	Search Space
Global	Random Seed	42 (Fixed)
	Validation Objective	RMSE
	Number of Trees (n_estimators)	[400, 1000]
	Maximum Depth (max_depth)	[10, 25]
	Minimum Samples Split	[15, 50]
	Minimum Samples Leaf	[5, 20]
Random Forest (50 BO iterations)	Max Features	{‘sqrt’, 0.4, 0.6}
	Number of Trees (n_estimators)	[800, 1500]
	Maximum Depth (max_depth)	[2, 6]
	Learning Rate	[0.01, 0.1] (Log-uniform)
	Subsample Ratio	[0.6, 0.9]
	Colsample By Tree	[0.6, 0.9]
XGBoost (50 BO iterations)	Minimum Child Weight	[20, 60]
	L1 Regularization (reg_alpha)	[0.1, 5.0] (Log-uniform)
	L2 Regularization (reg_lambda)	[0.1, 5.0] (Log-uniform)
	Early stopping Patience	50 rounds
	Input Window Length (time_steps)	[5, 30]
	Number of LSTM Layers	{1, 2}
LSTM (20 BO iterations)	Hidden Units (Layer 1)	[64, 256]
	Hidden Units (Layer 2)	[32, 128]
	Dense Layer Units	[32, 128]
	Dropout Rate	[0.1, 0.4]
	Optimizer	Adam

Learning Rate	[0.0005, 0.01] (Log-uniform)
L2 Regularization (weight_decay)	$[1 \times 10^{-6}, 1 \times 10^{-3}]$ (Log-uniform)
Batch Size	{32, 64, 128}
Maximum Epochs/Patience	200 epochs/30 epochs

2.4. Performance Evaluation Metrics

We evaluate the HHT-SR-ML framework across three dimensions: goodness-of-fit, absolute error magnitude, and hydrological consistency. The evaluation uses six standard indices: Adjusted Coefficient of Determination (Adjusted R^2), Nash-Sutcliffe Efficiency (NSE), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Kling-Gupta Efficiency (KGE), and Percent Bias (PBIAS).

(i) Goodness-of-Fit and Global Accuracy: Adjusted R^2 measures the proportion of variance in the observed data explained by the model while accounting for the number of input features. For brevity, the Adjusted R^2 is denoted simply as R^2 throughout the remainder of this manuscript. NSE benchmarks the model's predictive skill against the mean observation.

(ii) Absolute Error Magnitude: RMSE heavily penalizes large prediction errors. This sensitivity highlights the model's performance during extreme hydrological events, such as summer flood peaks. MAE calculates the average absolute difference between predictions and observations, reflecting baseline simulation precision.

(iii) Hydrological Consistency and Mass Balance: KGE decomposes the overall error into correlation, bias, and variability components. This decomposition addresses NSE's known tendency to underestimate peak flows. PBIAS quantifies the water mass balance to identify any systematic tendency of the model to overestimate or underestimate stream-flow.

The mathematical formulations for these metrics are defined as follows:

$$R_{\text{adj}}^2 = 1 - \frac{(1 - R^2)(n - 1)}{n - k - 1} \quad (16)$$

$$\text{NSE} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (17)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2} \quad (18)$$

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |\hat{y}_i - y_i| \quad (19)$$

$$\text{KGE} = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (20)$$

$$\text{PBIAS} = 100 \times \frac{\sum_{i=1}^n (\hat{y}_i - y_i)}{\sum_{i=1}^n y_i} \quad (21)$$

In these expressions, $\hat{y}_i$ and y_i denote the predicted and observed values, respectively. The term r represents the Pearson correlation coefficient. The parameters $\alpha = \sigma_{\hat{y}}/\sigma$ and $\beta = \mu_{\hat{y}}/\mu$ denote the variability ratio (ratio of standard deviations) and the bias ratio (ratio of means) between the predicted and observed series, respectively.

3. Results

3.1. Hydro-Meteorological Trends and Abrupt-Change Analysis

To evaluate the temporal evolution of the hydro-meteorological series while accounting for the effects of serial autocorrelation, we applied the Hamed-Rao modified Mann-Kendall (MK) trend test, Sen's slope estimator, and abrupt change analysis to the 2007–2024 observational data (Figure 3 and Table 2). This step assesses the non-stationarity within the dataset, which presents inherent challenges for data-driven modeling.

The analysis indicates that the meteorological drivers of the upper Yellow River have exhibited non-stationarity over the past two decades. Based on the modified MK test (Table 2), Temperature (TEM) and Wind Speed (Wind) recorded significant upward trends, with Z-statistics of 3.26 ($p < 0.01$) and 3.40 ($p < 0.001$), and Sen's slopes of 0.067 and 0.037, respectively. Relative Humidity (RHU) showed a decreasing trend ($Z = -2.93$, $p < 0.01$, slope = -0.265), while Potential Evapotranspiration (PET) increased ($Z = 2.27$, $p < 0.05$, slope = 0.013). This climatic shift toward a warmer and drier baseline introduces complex non-linear dynamics into the basin's hydrological cycle. Conversely, Streamflow (Flow) and Precipitation (PRE) did not exhibit statistically significant directional trends. Instead, they displayed stochastic fluctuations, indicating a hydrological response characterized by high variance. This complexity complicates direct predictive modeling using raw inputs.

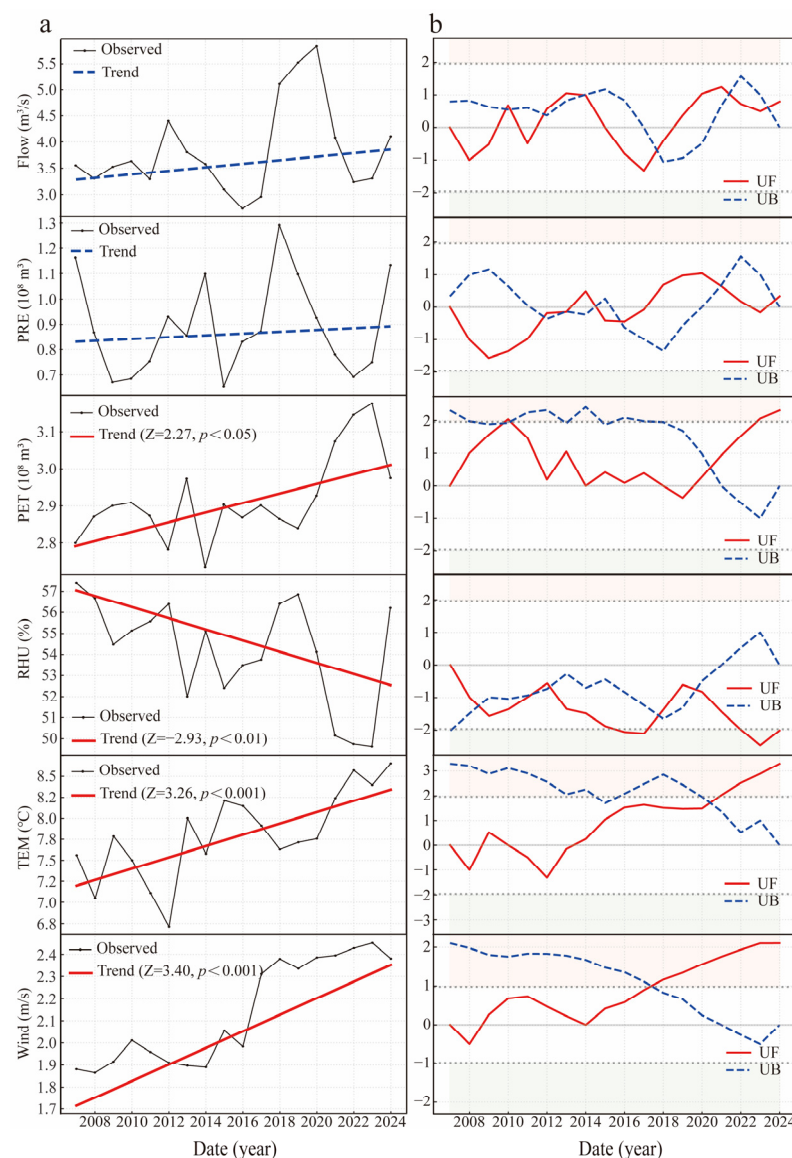


Figure 3. Trend and abrupt-change analysis of hydro-meteorological series in the Lanzhou section of the Yellow River from 2007 to 2024. **(a)** Mann–Kendall trend test results for Flow, Precipitation (PRE), Potential Evapotranspiration (PET), Relative Humidity (RHU), Temperature (TEM), and Wind Speed (Wind). The red lines indicate statistically significant trends, while blue dashed lines indicate non-significant trends. Note the significant warming (TEM) and increasing wind speed trends. **(b)** Mann–Kendall abrupt change test (M-K) showing the sequential (UF, red) and reverse (UB, blue) statistic curves. The orange and green shaded areas represent the upper and lower 95% confidence intervals.

Table 2. Trend analysis of hydrometeorological variables using the Hamed-Rao modified Mann–Kendall test. (The Hamed-Rao modification was applied to the standard Mann–Kendall (MK) test to account for serial autocorrelation in the time series by adjusting the variance and significance. The magnitude of the trends is quantified using Sen’s slope estimator. The significance level is evaluated at $\alpha = 0.05$).

Variable	Trend	Significant	<i>p</i> -Value	Z-Value	Sen’s Slope
Flow	No Trend	FALSE	\	\	3395.7845
PET	Increasing	TRUE	0.0230	2.2727	0.0129
PRE	No Trend	FALSE	0.6115	0.5079	0.0036
RHU	Decreasing	TRUE	0.0034	−2.9309	−0.2648
TEM	Increasing	TRUE	0.0009	3.2575	0.0673
Wind	Increasing	TRUE	0.0007	3.3979	0.0375

3.2. Intrinsic Mode Decomposition and Target Frequency Identification

We applied the Hilbert-Huang Transform (HHT) to the non-stationary streamflow series. This step isolates intrinsic oscillatory components and establishes a precise target for signal enhancement. Figure 4 details the decomposition results, along with their Center Frequencies (FF) and Variance Contribution Ratios (CR). The HHT decomposed the streamflow series into 10 Intrinsic Mode Functions (IMFs) and a residual trend. High-frequency components (IMF1 to IMF5) display rapid stochastic oscillations. Their energy contribution, however, is minimal, with each accounting for less than 6% of the total variance. These rapid fluctuations primarily reflect background noise or short-term surface disturbances. They do not represent the basin’s dominant hydrological variations.

The system’s energy primarily concentrates in the low-frequency modes. IMF7 and IMF6 dominate the variance spectrum, contributing 44.2% and 34.2%, respectively. The variance contributions of IMF7 (44.2%) and IMF6 (34.2%) were determined using the CEEMDAN framework. By generating multiple signal realizations with added Gaussian noise and averaging the outcomes, the CEEMDAN algorithm inherently serves as a robustness check, ensuring that these variance contributions and the identified frequencies are stable and resilient to noise artifacts. Together, they account for over 78% of the total streamflow variability. In the context of HHT decomposition, variance represents the energetic contribution of each component to the overall system dynamics. The extracted residual trend physically reflects the long-term, non-periodic monotonic shifts within the basin, such as the gradual drying and warming climate regime. Because it lacks periodicity, it cannot serve as a resonant target. This high variance concentration in IMF6 and IMF7 indicates that the basin’s hydrological evolution is not entirely stochastic. Instead, latent low-frequency periodic signals—centered at $f_d = 0.0026 \text{ d}^{-1}$ and 0.0043 d^{-1} —characterize the underlying temporal dynamics. We applied the principle of variance dominance to establish a target for the data enhancement phase. By utilizing this principle, we systematically filter out both the non-periodic residual trend and the low-energy, high-frequency stochastic noise (IMF1–IMF5). We designated the most energetic mode (0.0026 d^{-1}) as the system’s characteristic frequency. This specific parameter captures the dominant periodic

characteristic of the streamflow series, providing the reference target for frequency matching in the subsequent Stochastic Resonance optimization.

It is important to highlight the hydrological relevance of the extracted dominant characteristic frequency ($f_d = 0.0026 \text{ d}^{-1}$). In the time domain, this frequency corresponds to a period of approximately 384 days ($T = 1/f_d$), which closely mirrors the annual seasonal hydrological cycle inherent to the Lanzhou section of the upper Yellow River (driven by summer monsoons and spring snowmelt). From a hydrological perspective, a river basin acts as a natural macro-scale low-pass filter: high-frequency, noisy meteorological inputs (e.g., erratic daily precipitation) are buffered by soil infiltration and groundwater routing, ultimately yielding a smoothed, low-frequency streamflow response. Therefore, selecting this specific HHT-derived frequency as the target for the Stochastic Resonance (SR) system provides a hydrologically justified reference. It essentially sets the basin's 'natural rhythmic pulse' as an attractor. This process induces resonance in noisy meteorological variables at the dominant characteristic frequency identified from historical streamflow data, transferring the energy of high-frequency stochastic meteorological noise into low-frequency periodic components that better represent the dominant low-frequency characteristics of the basin's runoff routing process.

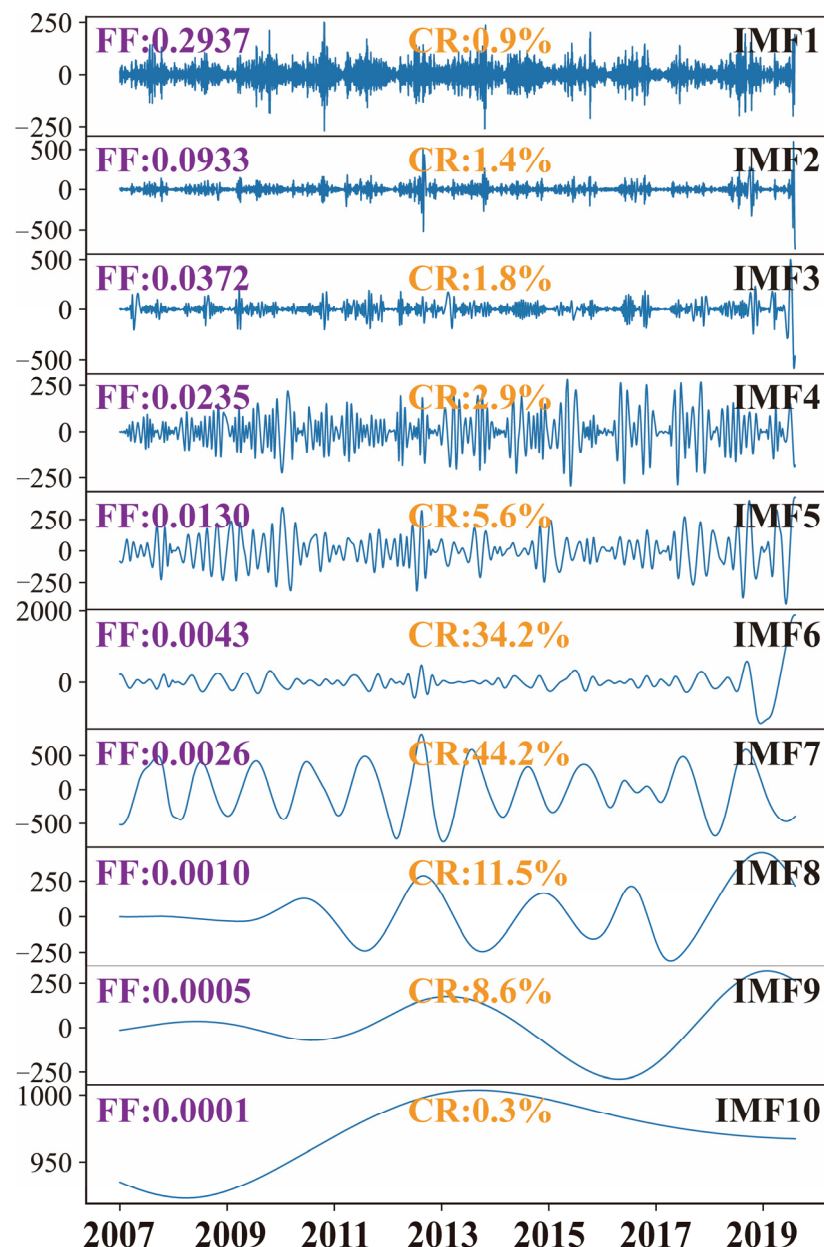


Figure 4. Multi-scale decomposition of the streamflow time series using the CEEMDAN-based Hilbert-Huang Transform (HHT). The subplots display the 10 Intrinsic Mode Functions (IMF1–IMF10) extracted from the streamflow data. FF denotes the energy-weighted center frequency (cycles/day) of each component, and CR denotes the variance contribution ratio (%). The system's variance is predominantly concentrated in the low-frequency components IMF6 (CR = 34.2%) and IMF7 (CR = 44.2%). The representative frequencies of these dominant modes are utilized as the target characteristic frequencies for the subsequent Stochastic Resonance (SR) enhancement module. (Note: The data displayed in this figure corresponds strictly to the training subset to prevent data leakage, with the temporal axis slightly adjusted for visual alignment.)

3.3. Signal Enhancement via Stochastic Resonance-Reconstructing Energy

We used the characteristic frequency from Section 3.2 to guide the Bayesian optimization of the Stochastic Resonance (SR) system. This calibration dynamically adjusts the system parameters to enhance the periodic components of the meteorological inputs, rather than applying standard smoothing filters. Figure 5 details the time-domain waveforms and frequency-domain Power Spectral Density (PSD) for key meteorological factors before and after SR enhancement.

Time-domain plots (Figure 5a) show high-frequency stochastic fluctuations obscuring the raw meteorological data (orange lines). This disordered background noise heavily affects Precipitation (PRE) and Wind Speed (Wind). After SR processing (blue lines), the data exhibit distinct bistable transition characteristics. The nonlinear SR system rescales the signal amplitude to extract a clear periodic profile, shifting the signal between potential wells using the high-frequency noise.

Frequency-domain analysis (Figure 5b) illustrates the underlying energy transfer mechanism. The power spectra of the raw data (orange lines) distribute flatly across the frequency band, reflecting scattered energy. Following SR enhancement (blue lines), energy density increases distinctly within the low-frequency domain. To quantitatively evaluate this enhancement beyond visual PSD inspections, Table 3 presents the initial and enhanced Signal-to-Noise Ratios (SNR), the Spectral Amplification Factor (SAF), and the Pearson correlation coefficient (r).

As shown in Table 3, the SR system yielded SNR gains ranging from 9.70 dB to 20.03 dB across the meteorological features. The SAF values, generally greater than 1, mathematically indicate that high-frequency environmental noise was harvested and transferred to the target frequency, distinguishing this process from traditional linear filtering which typically dissipates energy. Furthermore, the Pearson correlation coefficients (r) reflect varying degrees of temporal waveform retention. Features with inherent periodicities, such as PET ($r = 0.81$), retained a high correlation with their original temporal profiles. Conversely, highly stochastic signals like PRE ($r = 0.47$) and Wind ($r = 0.02$) exhibited lower correlations, indicating that the SR system primarily extracted the hidden dominant low-frequency periodicity rather than strictly preserving the original noisy temporal fluctuations. This precise frequency matching aligns the meteorological inputs more closely with the target streamflow's inherent rhythm.

While the SR mechanism effectively reshapes the noisy meteorological variables into bistable, low-frequency periodic profiles, it is critical to clarify the interpretation of these transformed signals. Regarding the magnitudes and the presence of negative values, the SR-transformed variables should no longer be interpreted as absolute physical quantities. Due to the inherent mathematical nature of the bistable potential well used in the SR system, the transformed signals oscillate between distinct high and low states. Consequently, the outputs act as dimensionless hydro-climatic input anomalies. In this context, positive peaks represent the accumulation of effective meteorological signal energy, whereas negative values do not represent unphysical negative rainfall, but rather denote a relative

energy deficit or a baseline dry phase within the basin's natural rhythm. By conceptualizing these inputs as physics-inspired anomalous forcing indices rather than mass-conserved absolute variables, the framework provides highly informative, rhythmically aligned predictors for the deep learning algorithms while avoiding interpretative contradictions.

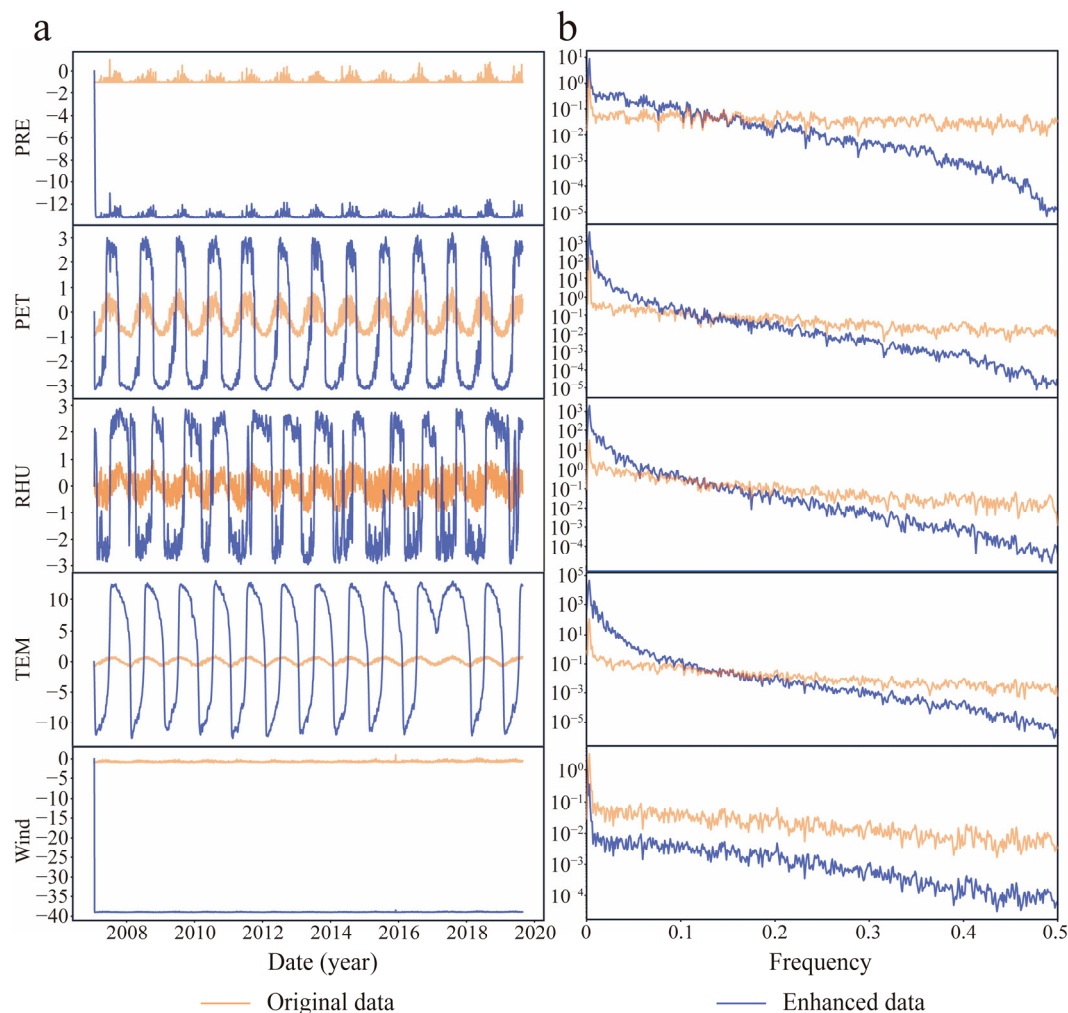


Figure 5. Comparison of meteorological driving factors before and after Stochastic Resonance (SR) enhancement. **(a)** Time-domain waveforms of PRE, PET, RHU, TEM, and Wind. The orange lines represent the raw observational data, while the blue lines denote the SR-enhanced signals. These transformed signals function as dimensionless anomalous forcing indices, exhibiting bistable transition characteristics and reconstructed low-frequency periodicities. **(b)** Power Spectral Density (PSD) analysis. The SR mechanism (blue) actively transfers high-frequency noise energy from the raw data (orange) to the targeted low-frequency domain ($f < 0.1$ cycles/day), achieving frequency synchronization with the intrinsic hydrological rhythm. (Note: The data displayed in this figure corresponds strictly to the training subset to prevent data leakage during parameter optimization, with the temporal axis slightly adjusted for visual presentation.)

Table 3. Quantitative evaluation metrics of meteorological features before and after Stochastic Resonance (SR) enhancement. The table presents the initial and enhanced Signal-to-Noise Ratios (SNR), SNR Gain (Δ SNR), Spectral Amplification Factor (SAF), and Pearson correlation coefficient (r). A SAF value significantly greater than 1 mathematically verifies the active harvesting and transfer of high-frequency noise energy to the target frequency. The varying r values reflect the system’s adaptive behavior: extracting dominant low-frequency periodicity from highly stochastic inputs while preserving the temporal profiles of features with inherent rhythmic trends.

Feature	Initial SNR (dB)	Enhanced SNR (dB)	SNR Gain (dB)	SAF	r
PET	25.80	39.75	13.96	28.56	0.81
PRE	8.73	18.42	9.70	7.20	0.47
RHU	17.71	35.31	17.60	36.80	0.55
TEM	29.78	49.82	20.03	50.86	0.30
Wind	14.87	25.22	10.35	0.78	0.02

3.4. Comparative Analysis of Model Performance

We evaluated the physics-inspired enhancement framework across three distinct machine learning architectures: RF, XGBoost, and LSTM. Both the SR-enhanced and raw meteorological datasets served as model inputs.

We evaluated the models’ ability to capture complex dynamics using time-series hydrographs (Figure 6a). Baseline models frequently exhibited temporal lags and underestimated flows during extreme hydrological events, such as summer flood peaks. The SR-LSTM model, by contrast, more accurately tracked the rapid rising and receding limbs of these hydrographs. Scatter density plots (Figure 6b) confirm this enhanced peak-capture capability. The SR-LSTM regression slope ($k = 0.88$) aligns closely with the 1:1 ideal line. These results show that the SR mechanism effectively mitigates the common peak-shaving and valley-filling problem in traditional data-driven models.

To quantitatively substantiate this visual observation, Table 4 presents specialized evaluation metrics for the high-flow regime (flows exceeding the 90th percentile, Q90) and discrete peak events. While data-driven models typically suffer from severe peak underestimation due to regression to the mean, the SR-enhanced models maintained robust accuracy under high-water conditions. All models achieved NSE_Q90 values exceeding 0.83, with the LSTM architecture performing the best (NSE_Q90 = 0.89). Crucially, the relative errors for peak magnitudes (Peak_Error %) were remarkably constrained to −5.08%, −6.32%, and −6.09% for LSTM, XGBoost, and RF, respectively. Although an expected slight negative bias (underestimation) persists, these low percentage errors indicate that the SR preprocessing successfully provides sufficient low-frequency amplitude information for the models to reconstruct extreme flow events without severe numerical attenuation.

The Taylor Diagram (Figure 7) maps the models’ statistical fidelity. The SR-LSTM model (purple inverted triangle) positions closest to the empirical observation point (black star). It achieves the highest correlation alongside the lowest Root Mean Square Difference (RMSD). This spatial clustering indicates that frequency matching via stochastic resonance effectively enables neural networks to better capture and represent the dominant statistical variability embedded in the hydrological system, rather than merely adjusting overall data variance.

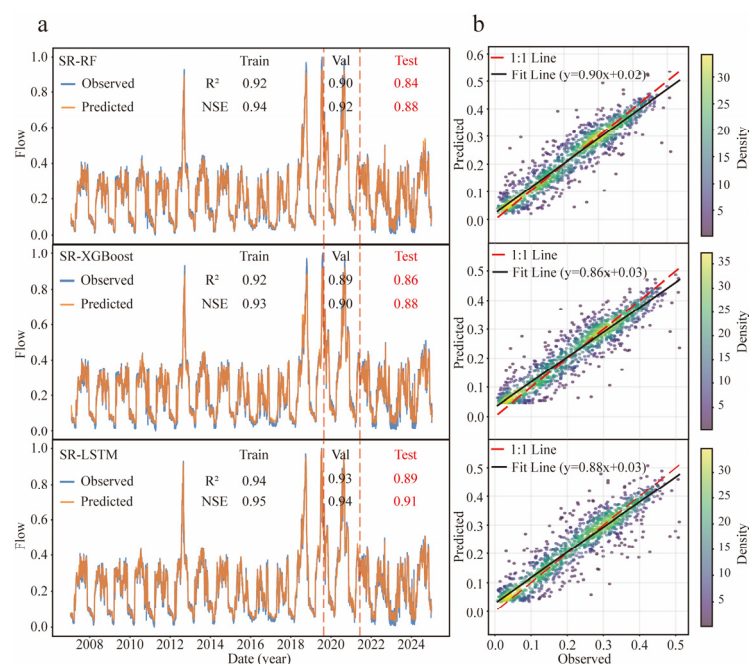


Figure 6. Streamflow simulation results of the SR-enhanced machine learning models on the test set. (a) Comparison of observed (blue) and predicted (orange) streamflow hydrographs for SR-RF, SR-XGBoost, and SR-LSTM models. The dashed vertical lines delineate the training, validation, and testing periods. (b) Density scatter plots of observed versus predicted streamflow. The black solid line represents the linear fit, and the red dashed line represents the 1:1 ideal line. The color gradient indicates the data point density.

Table 4. High-flow and peak-flow evaluation metrics for the three machine learning architectures on the testing set. The evaluation focuses on the high-flow regime (flows exceeding the 90th percentile, Q90) and discrete extreme peak events. The low relative peak magnitude errors (Peak Error %) demonstrate the models' capability to mitigate the common underestimation issue in data-driven forecasting during extreme hydrological conditions.

Model	NSE Q90	RMSE Q90	MAE Q90	PBIAS Q90 (%)	Peak Error	Peak Error (%)
RF	0.83	148.79	137.39	5.16	−111.57	−6.09
XGBoost	0.87	134.88	125.02	4.77	−73.81	−6.32
LSTM	0.89	131.52	114.71	3.03	−65.73	−5.08

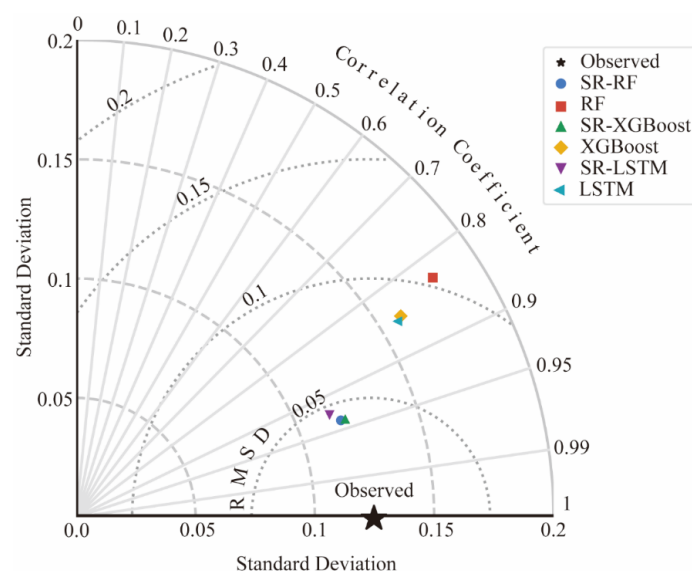


Figure 7. Taylor diagram illustrating the statistical performance of the six models (SR-RF, RF, SR-XGBoost, XGBoost, SR-LSTM, LSTM) against the observed streamflow data (black star). The radial distance represents the standard deviation (SD), the angular position represents the correlation coefficient, and the concentric dashed arcs represent the centered root-mean-square difference (RMSD). The SR-LSTM model (purple inverted triangle) is positioned closest to the observation point, indicating it has the highest correlation and lowest error, effectively reproducing the variability of the hydrological process.

3.5. Robustness, Ablation, and Benchmark Analysis

To evaluate the methodological consistency of the proposed framework and explore the relative contributions of different input features, we conducted a comprehensive assessment. Deep learning models often exhibit performance variance due to weight initialization and stochastic training processes. To ensure statistical robustness, all deep learning models were executed across 30 independent runs with varying random seeds. The integrated results, including feature ablation and preprocessing benchmark comparisons, are reported in Table 5 in the format of Mean $\pm$ Standard Deviation (SD). The SR-LSTM model yielded an average NSE of 0.91 ± 0.03 , compared to an NSE of 0.79 ± 0.02 for the baseline LSTM. This relatively narrow variance suggests that the enhanced predictive performance is a consistent property of the model configuration rather than an artifact of a specific random seed. Furthermore, a Wilcoxon signed-rank test was conducted on the prediction residual errors between the baseline and SR-enhanced models. The test resulted in a p -value of <0.01 , indicating that the difference in predictive performance is statistically significant.

To investigate the potential over-reliance on the autoregressive term (R_{lag1}), we systematically ablated the input variables. The Lag-only LSTM achieved a moderate NSE of 0.76 ± 0.04 . This indicates that while streamflow persistence provides a foundational memory for the model, relying exclusively on it may limit the capacity to respond to more complex or rapid hydro-climatic variations. To assess the effect of the Stochastic Resonance (SR) mechanism, we compared the predictive performance of meteorological inputs with and without SR enhancement. The Raw Meteorology-only LSTM (operating without streamflow data) achieved an NSE of 0.33 ± 0.02 . In comparison, the SR-Meteorology-only LSTM achieved an NSE of 0.53 ± 0.04 . These results indicate that the SR framework provides more informative meteorological inputs compared to raw data. Furthermore, because the combined SR-LSTM exhibits significantly improved performance compared to the baseline LSTM, it suggests that the SR-enhanced meteorological variables serve as dynamic predictors that complement the autoregressive term to improve overall model responsiveness.

We further compared the SR framework against alternative traditional preprocessing techniques. The MA-LSTM (7-day moving average) yielded an NSE of 0.71 ± 0.02 , implying that simplistic smoothing might inadvertently obscure critical signal variance. The WT-LSTM (using Wavelet Transform) improved the performance (NSE = 0.79 ± 0.01), yet the proposed SR-LSTM exhibited higher accuracy. This comparison suggests that actively leveraging stochastic resonance to harmonize meteorological inputs with the basin's characteristic rhythm serves as a highly effective alternative to traditional destructive filtering, supporting more robust streamflow estimations.

Table 5. Comprehensive evaluation of model robustness, feature ablation, and preprocessing benchmarks. R_{lag1} denotes the one-step lagged streamflow. MA represents the 7-day Moving Average smoothing; WT denotes Wavelet Transform; SR denotes Stochastic Resonance; SD stands for Standard Deviation. All deep learning models (LSTM variants) were evaluated across 30 independent random seed initializations to account for stochastic variance in model training.

Model	Input Features	R ² (Mean ± SD)	NSE (Mean ± SD)
MA-LSTM (7-day)	Raw Met + R _{lag1}	0.63 ± 0.01	0.71 ± 0.02
WT-LSTM (Wavelet)	WT Met + R _{lag1}	0.72 ± 0.04	0.79 ± 0.01
Lag-only LSTM	R _{lag1}	0.61 ± 0.02	0.76 ± 0.04
Meteorology-only LSTM	Raw Met	0.25 ± 0.05	0.33 ± 0.02
SR-Meteorology-only LSTM	SR-Met	0.45 ± 0.03	0.53 ± 0.04
LSTM	Raw Met + R _{lag1}	0.76 ± 0.01	0.79 ± 0.02
SR-LSTM	SR-Met + R _{lag1}	0.89 ± 0.01	0.91 ± 0.03

4. Discussion

4.1. Mechanism of Resonance-Induced Enhancement: Extracting Signal from Noise

This study introduces a different approach to handling hydro-meteorological noise using the Stochastic Resonance (SR) mechanism. Traditional signal processing methods, such as moving-average smoothing or wavelet denoising, treat high-frequency noise strictly as interference. They mathematically filter it out [34,35]. These destructive filtering methods stabilize data but often discard valuable high-frequency signal variance during extreme hydrological events. This loss directly causes the common peak-shaving problem in subsequent predictions [36,37]. Our frequency-domain analysis (Figure 5b) demonstrates an alternative signal enhancement approach.

The SR system does not eliminate noise. It leverages a non-linear bistable potential well to rectify the energy of high-frequency stochastic perturbations in the meteorological inputs [29]. Figure 5b shows that the flatly distributed noise background in the raw data does not vanish after enhancement. The system transfers and condenses this energy into the low-frequency domain ($f < 0.1$). This shift verifies the energy transfer mechanism. Noise serves as an active energy source to amplify weak, latent periodic signals rather than a nuisance to be removed [28,38]. We anchored the SR system's parameters to the streamflow's characteristic frequency (extracted via HHT). This alignment induces a targeted frequency resonance between the meteorological inputs and the hydrological response. The resonance effect effectively reconstructs climatic periodic patterns, such as authentic seasonal cycles of precipitation and evapotranspiration, previously hidden by stochastic fluctuations. Reconstructing these patterns significantly lowers the optimization difficulty for downstream machine learning models.

4.2. Feature Importance Analysis

High predictive accuracy often masks the black-box nature of deep learning models. We applied feature importance analysis (Figure 8) to investigate their internal predictive reliance. To ensure methodological consistency across all architectures (RF, XGBoost, and LSTM), feature importance was quantified using Permutation Importance calculated on the testing set. This approach measures the decrease in model performance when a feature's values are randomly shuffled, providing a robust and comparable metric for evaluating the contribution of each input variable to the model's predictive accuracy. The results suggest that the proposed SR-ML framework captures predictive patterns that are generally consistent with hydrological processes [39,40].

Lagged Streamflow (R_{lag1}) makes the highest predictive contribution across all three model architectures. This pattern reflects the temporal persistence of basin systems, where current discharge is highly correlated with antecedent states [41,42]. Examining the meteorological drivers provides further heuristic insights. Excluding the autoregressive term reveals that the SR-enhanced meteorological factors (e.g., PRE_{enhanced}, TEM_{enhanced}, PET_{enhanced}) rank highly in the feature importance hierarchy.

Figure 8c details this hierarchy for the LSTM model. PRE_enhanced acts as the primary meteorological predictor. This indicates that the model's predictions are highly sensitive to precipitation inputs, which aligns with precipitation-runoff correlations. Similarly, the XGBoost model (Figure 8b) heavily weights PET_enhanced, reflecting a sensitivity to evapotranspiration factors typical of semi-arid regions like the upper Yellow River [43–45]. While high feature importance does not strictly prove physical realism, the prominence of these SR-enhanced features suggests that the mechanism provides functional inputs that the networks utilize to capture underlying hydro-meteorological correlations, rather than marginalizing them as mere mathematical artifacts [46,47].

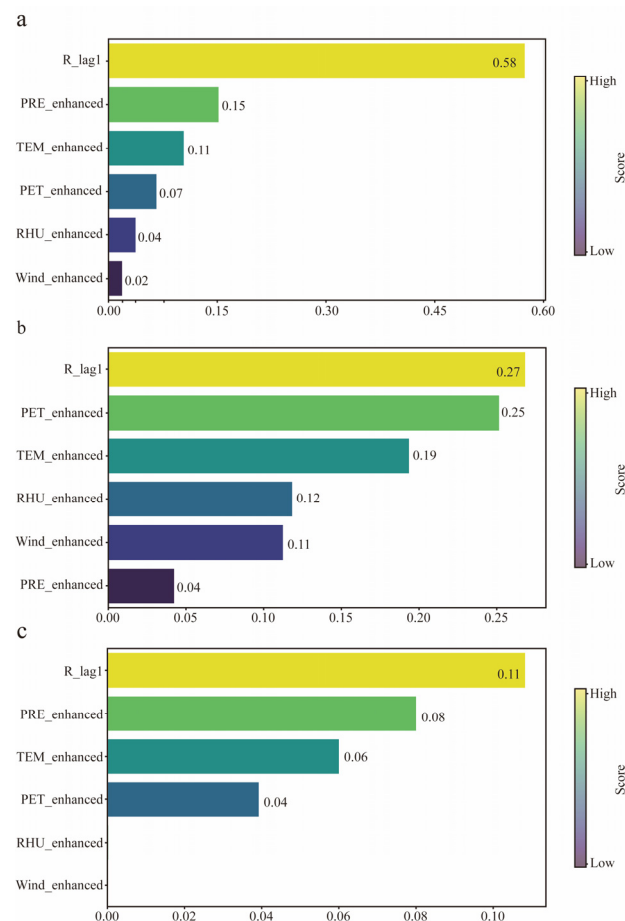


Figure 8. Feature importance rankings derived from the three machine learning models: (a) Random Forest (RF), (b) XGBoost, and (c) LSTM. The horizontal bars represent the relative contribution of each input variable to the model's predictive performance.

4.3. Impact of Model Architecture: The Structural Compatibility of LSTM

The SR mechanism improved predictive accuracy across all tested models. The extent of this improvement, however, depends heavily on the model architecture. Figure 9 details these differences. The SR-LSTM model increased its Nash-Sutcliffe Efficiency (NSE) from 0.79 to 0.91. Crucially, when evaluating the models on the inverse-transformed original measurement scale, the SR-LSTM model reduced the Root Mean Square Error (RMSE) from 178 m³/s (baseline LSTM) to 105 m³/s, and the Mean Absolute Error (MAE) from 115 m³/s to 97 m³/s. Given the baseline discharge characteristics of the Lanzhou section of the upper Yellow River, this reduction in absolute physical error, highlighted by a 73 m³/s drop in RMSE, demonstrates the framework's enhanced capability to capture high-flow dynamics. Furthermore, the true Percent Bias (PBIAS) calculated on the original scale re-

mained exceptionally low for both the baseline (1.21%) and the SR-LSTM (1.57%), confirming that the models rigorously maintain high statistical unbiasedness over the prediction period.

Tree-based ensemble models (RF, XGBoost) recorded moderate gains. This disparity relates directly to the structural compatibility between specific algorithms and the morphologically enhanced signals. Random Forest and XGBoost partition feature spaces using discrete, orthogonal splits. Their bagging and boosting mechanisms provide a high tolerance for high-frequency noise [48,49]. These ensemble models maintain reasonable baseline performance on raw data. The SR enhancement therefore provides only an incremental benefit for these tree-based architectures.

LSTM is a recurrent neural network (RNN) that relies on continuous temporal dependencies and smooth gradient propagation [50–52]. High-frequency stochastic jitter in raw meteorological data acts as adversarial noise during backpropagation. This noise disrupts the memory cells' ability to capture long-term trends and triggers gradient instability [53,54]. The SR mechanism amplifies signal intensity and reconstructs the periodic trajectory via bistable transitions (Figure 5a). This continuous, mathematically smooth, and temporally periodic sequence aligns strictly with the architectural strengths of LSTM [51,55,56]. The SR framework removes these temporal obstacles. The deep learning architecture can then allocate its computational capacity toward learning the complex non-linear dynamics of the hydrological process, rather than fitting stochastic background noise.

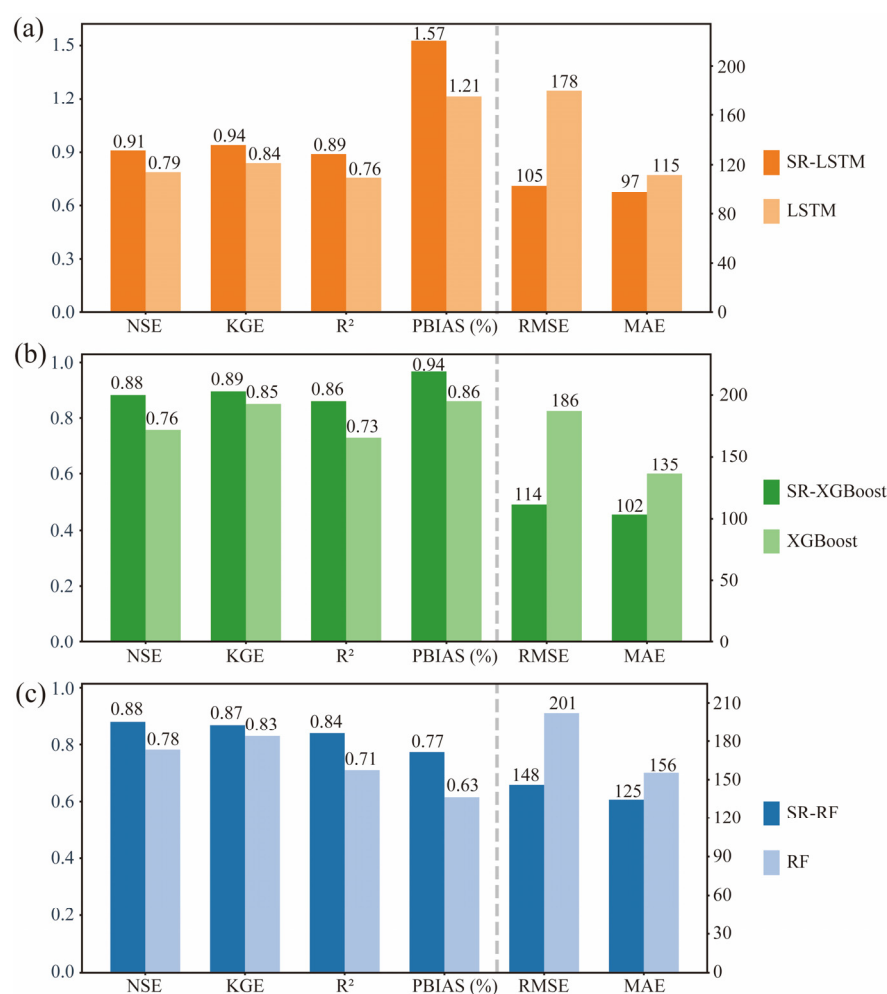


Figure 9. Performance comparison of different models in streamflow forecasting during the testing period. The bar charts display the evaluation metrics (NSE, KGE, R^2 , RMSE, MAE, and PBIAS) for SR-enhanced models (dark colors) versus original models (light colors). (a) LSTM comparison; (b)

XGBoost comparison; (c) Random Forest comparison. The gray dashed line separates efficiency metrics (higher is better) from error metrics (lower is better). The SR-LSTM model achieves the highest accuracy across all metrics (NSE = 0.91).

4.4. Limitations and Future Directions

The physics-inspired HHT-SR-ML framework effectively processes noisy geoscientific data, but specific limitations outline clear directions for future research. First, the current framework is strictly evaluated within a single basin, the Lanzhou section of the upper Yellow River. Hydrological processes exhibit strong spatial heterogeneity. The extracted characteristic frequency (f_0) and the optimized bistable system parameters (a , b) are inherently basin-specific, reflecting the unique local hydro-climatic regime. Therefore, the direct generalization of this exact parameter configuration to other basins with different topographies or climatic conditions is not guaranteed without re-calibration. Future research must rigorously test and adapt this framework across multi-basin scales, potentially integrating Spatiotemporal Graph Neural Networks (ST-GNNs) or Convolutional Neural Networks (CNNs) to extract both temporal resonance and spatial topological dependencies [57,58].

Second, the Bayesian optimization in this study statically calibrated the SR parameters based on historical training distributions. However, climate change introduces severe non-stationarity, making the characteristic frequency of future streamflow susceptible to concept drift [5,59,60]. Fixed SR parameters cannot sustain optimal resonance if future climatic regimes shift significantly away from historical patterns. Future work will develop adaptive stochastic resonance systems capable of real-time, online parameter calibration in response to dynamic input signals [61].

Finally, the framework entails high computational costs due to the sequential Bayesian optimization of both the SR system parameters and the subsequent deep learning hyperparameters. Furthermore, the enhancement efficacy is highly sensitive to the configuration of the bistable potential well; inappropriate parameter initialization can lead to signal attenuation rather than resonance. Future operational applications must balance optimization depth with computational efficiency, potentially through lightweight surrogate models or transfer learning.

Ultimately, the proposed physics-inspired data enhancement strategy provides a model-agnostic foundation, directly addressing the challenge of low signal-to-noise ratios common across complex environmental systems.

5. Conclusions

Climate change induces non-stationarity and high-frequency noise in hydro-meteorological data. We developed a physics-inspired data enhancement framework coupling the Hilbert-Huang Transform (HHT) with Stochastic Resonance (SR) to process these noisy inputs. Integrating this framework with diverse machine learning architectures (RF, XGBoost, and LSTM) in the upper Yellow River yields the following conclusions:

(i) Non-stationary Hydro-meteorological Evolution: Mann–Kendall analysis identified significant warming, drying, and intensified wind dynamics in the study area. These non-stationary shifts intensify the non-linearity of rainfall-streamflow relationships, constraining the reliability of traditional stationary models.

(ii) HHT-Guided Noise Utilization: HHT successfully isolated the basin's dominant characteristic frequency. Utilizing this as a target, the SR mechanism employs bistable transitions to redirect high-frequency stochastic noise into valid low-frequency periodic components, effectively facilitating frequency alignment between meteorological forcing and hydrological responses.

(iii) Multi-Model Predictive Accuracy: The physics-inspired enhancement of meteorological inputs improved performance across all tested machine learning architectures. The SR-LSTM model reached a Nash-Sutcliffe Efficiency (NSE) of 0.91. This score marks a nearly 20% improvement over the baseline LSTM. Notably, the framework maintained robust accuracy under high-water conditions, achieving a high-flow NSE of 0.89 and effectively mitigating the common peak-underestimation issue by constraining peak magnitude errors to approximately −5.08%.

(iv) Improved Representational Robustness: Feature importance analysis (via Permutation Importance) demonstrates that the framework reduces over-reliance on simple autoregressive extrapolation. By recovering key periodic patterns previously obscured by noise, the SR mechanism shifts predictive weight toward highly informative meteorological predictors (such as enhanced precipitation and evapotranspiration), thereby improving the statistical reliability and representational robustness of the model predictions.

This study moves beyond conventional single-model applications by embedding physics-inspired signal processing mechanisms (Stochastic Resonance) directly into the pre-processing stage of deep learning systems. Our findings suggest that the SR mechanism has the potential to transform meteorological noise, thereby improving the quality of input data for predictive models. The resulting physics-inspired data enhancement strategy provides a model-agnostic method for addressing the low signal-to-noise ratio bottleneck common in complex geoscientific and environmental expert systems.

Author Contributions: Methodology: Y.Q. and C.L.; Resources: C.L.; Data curation and Formal analysis: Y.Q.; Writing—original draft: Y.Q.; Writing—review and editing: C.L., X.Z., X.W., Q.L. and Y.Y.; Visualization: Y.Q.; Supervision: C.L. and X.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This study was financially supported by the National Natural Science Foundation of China (52579001, U2243236), the National Science Fund for Distinguished Young Scholars (52025092). The streamflow data were provided by the Yellow River Conservancy Commission (YRCC), and the meteorological forcing data were obtained from the China Meteorological Data Service Centre (CMDC).

Data Availability Statement: All data used in this study are publicly available, and are shared in <https://doi.org/10.6084/m9.figshare.31951806>.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal Relationships that could have appeared to influence the work reported in this paper.

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