

# Bayesian-optimized Support Vector Regression for Monthly Drought Estimation Using Rainfall and Large-scale Climate Teleconnections

Abhisek Kar<sup>1\*</sup>, Sujata Chakravarty<sup>1</sup>, Bibhuti Bhusan Sahoo<sup>2</sup>

<sup>1</sup>Department of Computer Science & Engineering, Centurion University of Technology and Management, Bhubaneswar, Odisha, India,

<sup>2</sup>Department of Agricultural Engineering, Centurion University of Technology and Management, Paralakhemundi, Odisha, India.

\*Corresponding Author's Email: abhisekkr300@gmail.com

## Abstract

This study developed a Bayesian-optimized support vector regression (SVR) framework for estimating one-month Standardized Precipitation Index (SPI-1) conditions at Kesinga station in the Tel River Basin, Odisha, India. Monthly rainfall for January 1981-December 2025 was obtained from the NASA POWER platform. Large-scale climate covariates comprised the Southern Oscillation Index (SOI), Niño 3.4 sea-surface-temperature anomaly, Dipole Mode Index (DMI) and Pacific Decadal Oscillation (PDO), while sine and cosine month terms represented annual seasonality. The 540-month record was separated chronologically into 70% training (January 1981-June 2012) and 30% testing (July 2012-December 2025). A conventional radial-basis-function SVR was compared with an Optuna-optimized SVR, for which the kernel and hyperparameters were selected over 100 trials using a tree-structured Parzen estimator and five-fold expanding-window time-series cross-validation. The original SVR produced test RMSE, MAE,  $R^2$ , NSE, correlation, bias and index-of-agreement values of 0.461, 0.347, 0.777, 0.777, 0.884, -0.053 and 0.932, respectively. The optimized SVR improved these values to 0.391, 0.302, 0.840, 0.840, 0.920, -0.056 and 0.958. Optimization reduced RMSE by 15.15% and MAE by 12.93%, while increasing  $R^2$  and NSE by 8.03%. Permutation analysis showed that rainfall and seasonal harmonics were the dominant predictors, whereas the teleconnection indices provided smaller but non-zero incremental contributions. Because contemporaneous rainfall was used to estimate same-month SPI-1, the framework is interpreted as drought-status estimation and monitoring rather than advance forecasting.

**Keywords:** Bayesian Optimization, Drought Monitoring, Optuna, Standardized Precipitation Index, Support Vector Regression, Tel River Basin.

## Introduction

Drought is a slowly developing hydroclimatic hazard whose effects can persist after precipitation returns to normal. In agriculture-dependent regions, short rainfall deficits can disrupt sowing, germination, supplemental irrigation, crop water availability and reservoir inflows. Objective monitoring is therefore essential where rainfall is strongly seasonal and decisions must respond to monthly anomalies. The Standardized Precipitation Index (SPI) is widely used because it expresses precipitation anomalies in standardized units and supports comparison across climates and accumulation periods (1). Its statistical properties and calculation procedures, including the influence of probability-distribution choice and record length, are well established (2, 3). This need is pronounced in the Tel River Basin of western Odisha. Basin-scale analysis has documented recurrent severe and extreme

droughts affecting agricultural and water-resource conditions in the Kalahandi region (4). Such historical exposure, combined with monsoon-dominated rainfall, makes short-timescale drought assessment operationally relevant. SPI-1 responds rapidly to current monthly precipitation, although adjacent values can change sharply. Temperature-sensitive indices such as SPEI provide complementary information when atmospheric water demand is important, but SPI remains a transparent precipitation-based benchmark for isolating rainfall deficits (5). Machine-learning methods can represent nonlinear relationships among hydroclimatic predictors. Recurrent neural networks have been used for SPEI forecasting (6). Climate-model ensemble experiments have demonstrated predictive value from atmospheric variables at explicit lead times (7). Remote-sensing and tree-based approaches also support multi-

This is an Open Access article distributed under the terms of the Creative Commons Attribution CC BY license (<http://creativecommons.org/licenses/by/4.0/>), which permits unrestricted reuse, distribution, and reproduction in any medium, provided the original work is properly cited.

(Received 08<sup>th</sup> July 2026; Accepted 01<sup>st</sup> October 2026; Published 26<sup>th</sup> October 2026)

source drought monitoring (8). These studies expose an important distinction: when rainfall from the target month is used to estimate SPI for that same month, the task is drought-status estimation or monitoring rather than advance forecasting. This terminology is adopted throughout the present study. For drought applications, reported accuracy must be interpreted against the information available at prediction time, the temporal validation design and the physical position of each predictor in the drought-generation pathway. A model may reproduce an index accurately while offering little true lead-time information if a contemporaneous variable closely related to the target is included. This study therefore evaluates predictive skill together with feature importance, drought-category reproduction, residual behaviour and the distinction between monitoring and forecasting.

Support vector regression (SVR) is suitable for moderate environmental datasets because nonlinear kernels can capture complex relationships while structural risk minimization controls model complexity (9). SVR and related hybrid methods have been applied to SPI modelling and drought prediction (10-13). Performance nevertheless depends strongly on kernel choice and on  $C$ , epsilon and gamma. Bayesian optimization provides a reproducible alternative to ad hoc tuning. Optuna implements sequential search using the tree-structured Parzen estimator (14), while hyperparameter-optimization best practice requires tuning to be embedded within leakage-controlled validation (15). For time series, temporal order must be preserved because random shuffling can place adjacent observations in both training and validation sets. This is particularly relevant for the present 540-month record, for which highly parameterized deep architectures could introduce unnecessary variance without stronger evidence of generalization. A tuned kernel model also provides a clear benchmark against which more complex future models can be assessed under the same chronological holdout conditions. The comparison between baseline and optimized SVR is therefore designed to test whether systematic tuning improves out-of-sample stability rather than merely reducing training error.

Large-scale ocean-atmosphere modes provide additional climatic context. Indian summer

monsoon variability is linked to ENSO and Indian Ocean variability, but teleconnection strength varies by season, lead time and model representation (16-18). Conceptually, SOI, Niño 3.4, DMI and PDO are treated here as distal climate-state indicators; local rainfall is the realized meteorological response; and SPI-1 is a standardized transformation of rainfall. This climate-state  $\rightarrow$  rainfall  $\rightarrow$  SPI pathway is critical for interpretation because high predictive importance does not imply direct causation by every teleconnection index.

The study uses NASA POWER rainfall because it offers accessible, reproducible monthly meteorological data for data-scarce applications. Its precipitation product has demonstrated practical hydrological utility (19), while comparative assessments over India show that gridded rainfall products can reproduce broad variability but may contain spatial or seasonal bias (20). Accordingly, NASA POWER is used as a reproducible input source rather than assumed to be error-free; independent validation against gauges and alternative products is identified as a priority for future operational use.

The specific research gap is that few studies combine chronology-preserving validation, Bayesian SVR hyperparameter optimization, contemporaneous rainfall, seasonal harmonics and large-scale teleconnection indices in a transparent SPI-1 drought-status framework for a drought-prone monsoon basin. The contribution is methodological, not a replacement for conventional SPI calculation. The objectives were to:

- a) construct a 1981-2025 Kesinga dataset integrating rainfall, SOI, Niño 3.4, DMI, PDO and seasonal harmonics;
- b) compare conventional and Optuna-optimized SVR using a fixed 70:30 chronological split and expanding-window cross-validation;
- c) quantify out-of-sample changes in error, efficiency, agreement and bias;
- d) interpret hyperparameter and predictor importance within the stated conceptual pathway; and
- e) examine reproduction of drought-category frequencies.

This design provides a reproducible monitoring benchmark and a defined foundation for future lead-time forecasting.

## Methodology

### Conceptual Framework and Experimental Design

The analysis follows an explicit predictive hierarchy: large-scale teleconnection indices represent distal climate-state information; monthly rainfall represents the local meteorological realization; seasonal harmonics represent calendar-dependent rainfall climatology; and SPI-1 is the standardized drought-status target. Because same-month rainfall is included, the model estimates contemporaneous drought status rather than future drought, as shown in

Figure 1. Model development was therefore designed to test whether Bayesian hyperparameter optimization improves stable reconstruction of SPI-1 while preserving temporal separation between training, validation and independent testing. The reproducibility framework also anticipates sensitivity checks against alternative precipitation products such as ERA5 and CHIRPS (21, 22). Indian evidence has also demonstrated regional precipitation-teleconnection coherence (23). Prior drought studies further support explicit hybrid or ensemble model comparisons (24).

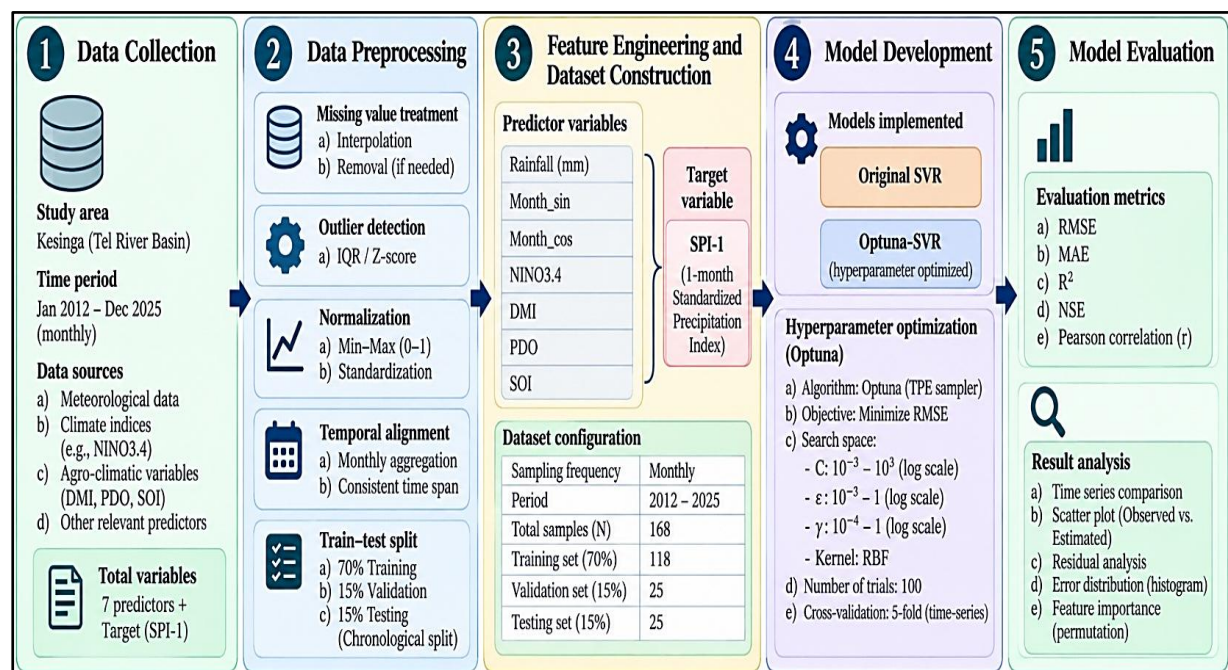


**Figure 1:** Experimental Design Framework for SPI-1 Drought-status Estimation

**Note:** SPI-1 = One-month Standardized Precipitation Index, SVR = Support Vector Regression, RMSE = Root Mean Square Error, MAE = Mean Absolute Error,  $R^2$  = coefficient of determination, NSE = Nash-sutcliffe Efficiency, SOI = Southern Oscillation Index, DMI = Dipole Mode Index, PDO = Pacific Decadal Oscillation.

Figure 1 summarizes the complete modelling workflow from data assembly to independent evaluation. The design preserves chronological order, separates the final 30% test period from model development and confines cross-validation to the training period. This structure minimizes temporal information leakage and clarifies that the output is same-month SPI-1 drought-status estimation rather than advance forecasting.

### Study Area

Kesinga is located in Kalahandi district of western Odisha within the Tel River Basin, a major tributary system of the Mahanadi (approximate GPS coordinates 20.2° N, 83.23° E). The basin has a

tropical monsoon climate with a concentrated wet season from June to September, a hot pre-monsoon period and a predominantly dry winter. Kesinga was selected because the surrounding Tel-Kalahandi region has documented recurrent drought exposure, including severe and extreme events that have affected agricultural and water-resource conditions (4). The local economy is strongly linked to rainfall-sensitive agriculture, so intra-seasonal rainfall variability and short dry spells are consequential even when seasonal totals appear near normal. The site also provides a continuous monthly climate record suitable for reproducible time-series modelling. A single-

station design avoids uncertainty introduced by spatial interpolation and permits direct evaluation of temporal model design; however, it does not represent the spatial heterogeneity of the wider Tel Basin and basin-wide application therefore

requires multi-station validation. Figure 2 locates Kesinga within the Tel River Basin and provides the geographic context for the station-specific analysis.

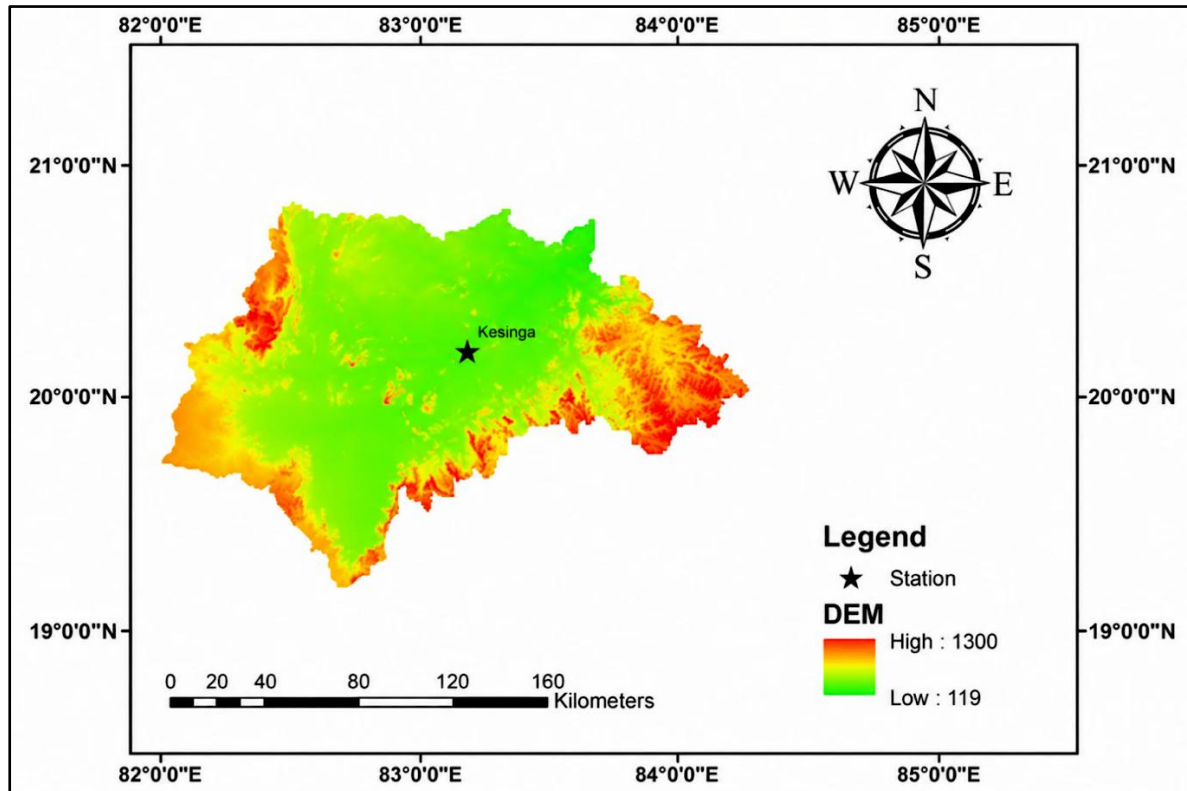


**Figure 2:** Geographical Location of Kesinga Station within the Tel River Basin, Odisha, India

**Note:** DEM = Digital Elevation Model. The star indicates the kesinga research site within the tel river basin.

Figure 2 provides the spatial context of the station-specific analysis within western Odisha. The location falls within the drought-prone Tel River Basin and represents the point for which the monthly hydroclimatic series was assembled. The map also shows the surrounding elevation pattern, which helps situate the site within the broader basin setting.

### Data Sources and Preprocessing

Monthly rainfall from January 1981 through December 2025 was obtained from the NASA POWER Data Access Viewer for the Kesinga location. The monthly series comprised 540 observations. Records were ordered chronologically, checked for duplicate dates, converted to numeric format and screened for missing values. No missing monthly observations remained after integration. NASA POWER was selected for reproducibility and continuous temporal coverage.

Nevertheless, product-related uncertainty is considered in the Discussion and future validation against gauge and alternative gridded products is recommended (19, 20). Alternative precipitation products proposed for future validation include ERA5 and CHIRPS (21, 22).

Four large-scale climate indices were incorporated. SOI represents the standardized pressure contrast between Tahiti and Darwin and characterizes the atmospheric component of ENSO; Niño 3.4 represents equatorial Pacific sea-surface-temperature anomalies and characterizes its oceanic component (16, 17). DMI represents the west-east tropical Indian Ocean temperature gradient associated with the Indian Ocean Dipole, while PDO describes lower-frequency North Pacific variability. All indices were aligned with the monthly rainfall series using a common year-month key. Related Indian studies have also quantified precipitation-teleconnection coherence at regional scales (23).

Two cyclic features were constructed to represent annual seasonality without creating an artificial discontinuity between December and January. For calendar month  $m$ , the seasonal features were defined using Equations [1] and [2].

$$\text{Month}_{\sin} = \sin\left(\frac{2\pi m}{12}\right) \quad [1]$$

$$\text{Month}_{\cos} = \cos\left(\frac{2\pi m}{12}\right) \quad [2]$$

These harmonic components enable the model to distinguish monsoon, post-monsoon, winter and pre-monsoon conditions while preserving circular continuity across the calendar year. The final predictor set comprised rainfall, SOI, Niño 3.4, DMI, PDO,  $\text{Month}_{\sin}$  and  $\text{Month}_{\cos}$ , with SPI-1 as the response variable

### Calculation of SPI-1 and Classification of Drought Conditions

SPI-1 was calculated from monthly rainfall by fitting a probability distribution separately for each calendar month so that strong rainfall seasonality was explicitly represented. Following the conventional SPI framework, the cumulative probability of precipitation was transformed to the standard-normal distribution.

For precipitation  $x$ , the mixed cumulative probability including zero rainfall is given in Equation [3].

$$H(x) = q + (1 - q)G(x) \quad [3]$$

Where  $q$  is the probability of zero precipitation and  $G(x)$  is the cumulative probability of positive rainfall under the fitted gamma distribution. The SPI value is then obtained using the inverse standard-normal transformation in Equation [4].

$$\text{SPI} = \Phi^{-1}[H(x)] \quad [4]$$

Where  $\Phi^{-1}$  denotes the inverse standard-normal cumulative distribution.

SPI values from -0.99 to +0.99 were classified as near normal; -1.00 to -1.49 as moderately dry; -1.50 to -1.99 as severely dry; and values  $\leq -2.00$  as extremely dry. Positive categories were defined symmetrically. Because SPI-1 is based on the target month's rainfall, it represents short-term meteorological drought status and can vary sharply between adjacent months.

### Chronological Training and Testing Design

The complete record was divided chronologically rather than randomly. The first 378 months (70%), January 1981-June 2012, formed the training dataset, while the remaining 162 months (30%), July 2012-December 2025, formed the independent testing dataset. The split boundary was fixed before model optimization. This design evaluates

whether relationships learned from the earlier climate period generalize to a later period and avoids leakage that can occur when temporally adjacent months are randomly allocated across training and testing sets (15). Figure 3 shows the observed SPI-1 series and the fixed chronological boundary used throughout model development and evaluation. This chronology-preserving principle is consistent with established guidance for time-series model evaluation (25).

Figure 3 demonstrates that the split was chronological rather than random. The earlier 378 months were used for model development, whereas the later 162 months were reserved for independent testing. This separation provides a more defensible assessment of temporal generalization and reduces leakage from adjacent monthly observations.

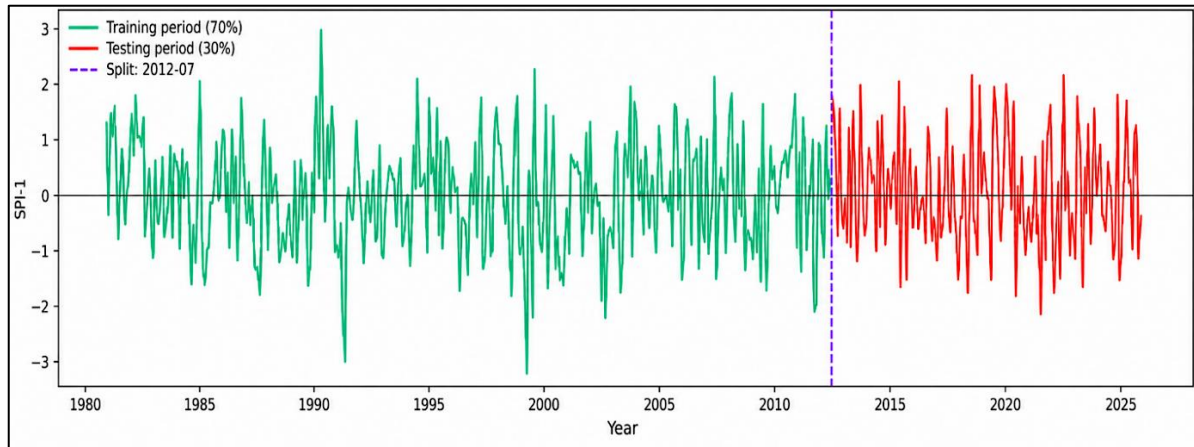


**Figure 3:** Chronological Division of the Observed SPI-1 Series into the 70% Training Period (January 1981–June 2012) and 30% Testing Period (July 2012–December 2025)

**Note:** SPI-1 = One-Month Standardized Precipitation Index. The vertical dashed line marks the fixed boundary between training and independent testing periods

Predictor scaling was implemented inside scikit-learn pipelines. For each predictor  $x$ , standardization was performed using Equation [5].

$$z = \frac{x - \mu_{\text{train}}}{\sigma_{\text{train}}} \quad [5]$$

Where  $\mu_{\text{train}}$  and  $\sigma_{\text{train}}$  are estimated only from the relevant training subset. During time-series cross-validation, each fold fitted its own scaler using that fold's training observations. This pipeline design prevents future observations from influencing feature scaling and thereby limits temporal information leakage (15).

### Support vector regression

SVR estimates a function  $f(x)$  that is as flat as possible while allowing errors within an epsilon-insensitive tube. Hybrid drought applications show that SVR performance can benefit from carefully validated model-combination strategies (24).

In a nonlinear kernel formulation, the prediction function is given in Equation [6].

$$f(x) = \sum_{i=1}^n (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad [6]$$

Where  $\alpha_i$  and  $\alpha_i^*$  are Lagrange multipliers,  $K$  is the kernel function and  $b$  is the intercept. The primal optimization objective is given in Equation [7].

$$\min \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n (\xi_i + \xi_i^*) \quad [7]$$

subject to deviations outside the epsilon tube being represented by slack variables  $\xi_i$  and  $\xi_i^*$ . The penalty parameter  $C$  controls the trade-off between model smoothness and errors outside the insensitive tube, while epsilon determines the width of that tube.

The radial-basis-function kernel is defined in Equation [8].

$$K(x_i, x_j) = \exp[-\gamma \|x_i - x_j\|^2] \quad [8]$$

gamma determines the effective spatial influence of individual training samples in feature space. Larger gamma values create more localized responses and can increase overfitting risk, whereas smaller values produce smoother response surfaces. The benchmark SVR used an RBF kernel with  $C = 10$ , epsilon = 0.10 and gamma determined by scikit-learn's 'scale' setting.

### Bayesian hyperparameter tuning

The optimized model was developed with Optuna using the Tree-structured Parzen Estimator sampler (14). The search space included RBF, polynomial and sigmoid kernels;  $C$  from  $10^{-2}$  to  $10^4$  on a logarithmic scale; epsilon from  $10^{-3}$  to 1; and gamma from  $10^{-5}$  to 10. Polynomial degree and coef0 were sampled conditionally when required. A total of 100 trials were conducted with

random seed 42. The optimization objective was mean RMSE across five expanding-window time-series folds within the training period. This

chronology-preserving design ensured that every validation fold occurred after its corresponding training observations.

For a validation set of  $n$  observations, RMSE was computed using Equation [9].

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad [9]$$

The best trial produced the lowest cross-validation RMSE (0.54549). The selected configuration used the RBF kernel with  $C = 9706.4209$ ,  $\epsilon = 0.3899069$  and  $\gamma = 0.0019159$ . The combination of high  $C$  and low  $\gamma$  indicates a smooth nonlinear response surface with strong

penalties for errors beyond a comparatively wide epsilon-insensitive region. Figure 4 summarizes the relative importance of the optimized hyperparameters and shows that  $\gamma$  and kernel choice exerted the strongest influence on the optimization objective.

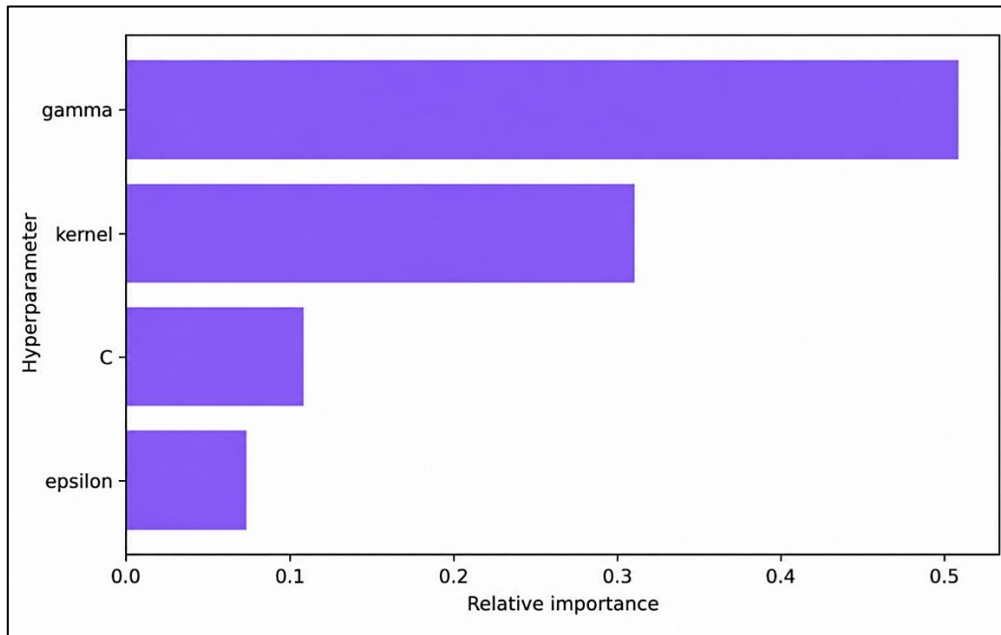


**Figure 4:** Optuna-derived Importance of Optimized SVR Hyperparameters

**Note:**  $C$  = SVR Penalty Parameter,  $\epsilon$  = Width of the Epsilon-Insensitive Tube,  $\gamma$  = Radial-basis-function Kernel Coefficient.

Figure 4 shows that  $\gamma$  and kernel choice contributed most strongly to the optimization objective, whereas  $C$  and  $\epsilon$  had smaller relative influence. The result indicates that response smoothness and kernel geometry were particularly important for generalization. The selected combination therefore reflects the interaction among regularization, tolerance and nonlinear feature-space structure.

MAE was calculated using Equation [10].

$$\text{MAE} = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad [10]$$

$R^2$  and NSE were computed from the same residual-sum-of-squares formulation and are therefore numerically identical for the same observed and predicted arrays, as given in Equation [11].

$$R^2 = \text{NSE} = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad [11]$$

## Performance evaluation

Training and testing performance were evaluated using RMSE, mean absolute error (MAE), coefficient of determination ( $R^2$ ), Nash-Sutcliffe efficiency (NSE), Pearson correlation, mean bias and Willmott's index of agreement. Using several complementary metrics avoids interpreting model quality from a single statistic.

Mean bias was calculated as predicted minus observed SPI averaged over all cases; negative bias therefore indicates systematic underestimation. Willmott's index of agreement was calculated using Equation [12].

$$d = 1 - \frac{\sum_{i=1}^n (\hat{y}_i - y_i)^2}{\sum_{i=1}^n (|\hat{y}_i - \bar{y}| + |y_i - \bar{y}|)^2} \quad [12]$$

Model improvement was expressed as percentage reduction for error metrics and percentage change for efficiency and agreement metrics. Permutation importance was estimated on the independent test set using 30 repeats; a predictor was considered influential when random permutation caused a larger deterioration in predictive performance. This test-set interpretation was used to distinguish dominant same-month predictors from variables that contributed only marginal incremental information.

## Results

### SPI-1 Time-Series Characteristics and Data Partitioning

The combined dataset comprised 540 monthly records from January 1981 to December 2025. The SPI-1 series exhibited rapid transitions between

wet and dry states, consistent with the high responsiveness of a one-month accumulation period. Moderate and severe droughts occurred repeatedly, whereas extreme drought months were rare. The temporal split retained 378 months for training and 162 months for testing; the test period extended for more than 13 years and therefore provided a substantive independent evaluation window. Figure 5 displays the full observed SPI-1 series together with the moderate, severe and extreme drought thresholds.

Figure 5 displays the high month-to-month variability expected for SPI-1 and identifies the timing of threshold exceedances. Moderate and severe drought conditions recur throughout the record, while extreme events are comparatively rare. This imbalance is relevant when interpreting model skill for uncommon high-severity drought categories.

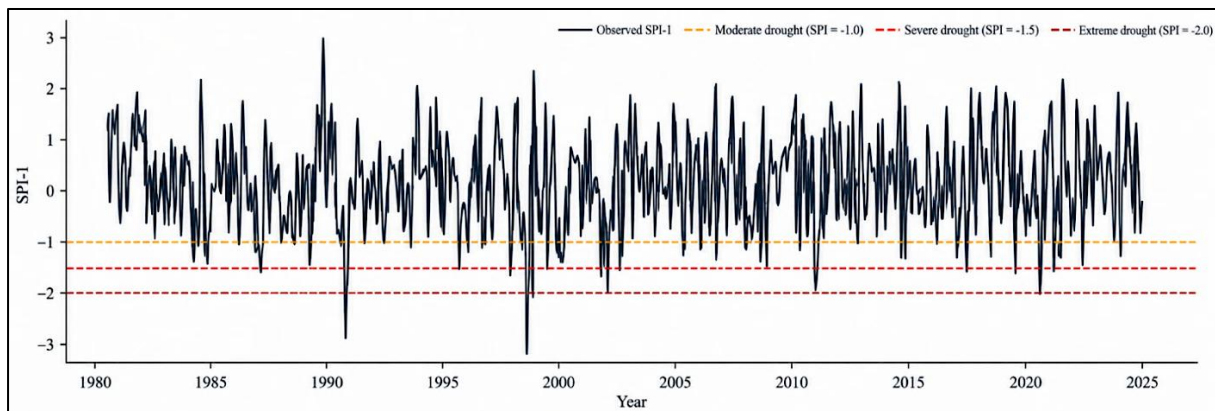


**Figure 5:** Observed Monthly SPI-1 Series for 1981–2025 with Moderate, Severe and Extreme Drought Thresholds

**Note:** SPI-1 = One-month Standardized Precipitation Index. Horizontal dashed lines denote moderate, severe, and extreme drought thresholds.

### Baseline and Optimized SVR Performance

Table 1 compares baseline and optimized SVR performance for both training and testing data. The baseline SVR fitted the training period closely (RMSE = 0.246;  $R^2$  = 0.936) but deteriorated on the independent test period (RMSE = 0.461;  $R^2$  = 0.777), indicating a clear generalization gap. In contrast, Optuna-SVR produced similar training and testing errors (RMSE = 0.390 and 0.391) and nearly identical  $R^2$  values (0.839 and 0.840). Thus,

optimization deliberately accepted weaker in-sample fit in exchange for substantially more stable out-of-sample performance.

On the independent test set, Optuna-SVR achieved RMSE = 0.391, MAE = 0.302,  $R^2$  = NSE = 0.840, correlation = 0.920, bias = -0.056 and index of agreement = 0.958. The average absolute error was therefore approximately 0.30 SPI units, while about 84% of test-period variance was reproduced. Figures 6-8 show the observed and model-estimated SPI-1 series for the full record,

training period and independent testing period, respectively. Across these views, the optimized model follows temporal variability more

consistently than the baseline, although departures remain around several high-magnitude wet and dry events.

**Table 1:** Evaluation Metrics of the Baseline and Optuna-Optimized SVR Models on the Training and Testing Datasets

| Model        | Dataset  | RMSE  | MAE   | R <sup>2</sup> | NSE   | Correlation | Bias   | Index of Agreement |
|--------------|----------|-------|-------|----------------|-------|-------------|--------|--------------------|
| Original SVR | Training | 0.246 | 0.154 | 0.936          | 0.936 | 0.969       | 0.025  | 0.982              |
| Original SVR | Testing  | 0.461 | 0.347 | 0.777          | 0.777 | 0.884       | -0.053 | 0.932              |
| Optuna-SVR   | Training | 0.390 | 0.308 | 0.839          | 0.839 | 0.917       | 0.001  | 0.953              |
| Optuna-SVR   | Testing  | 0.391 | 0.302 | 0.840          | 0.840 | 0.920       | -0.056 | 0.958              |

**Note:** RMSE = Root Mean Square Error, MAE = Mean Absolute Error, R<sup>2</sup> = coefficient of determination, NSE = Nash-Sutcliffe Efficiency, SVR = Support Vector Regression. Bias is calculated as predicted minus observed SPI-1.

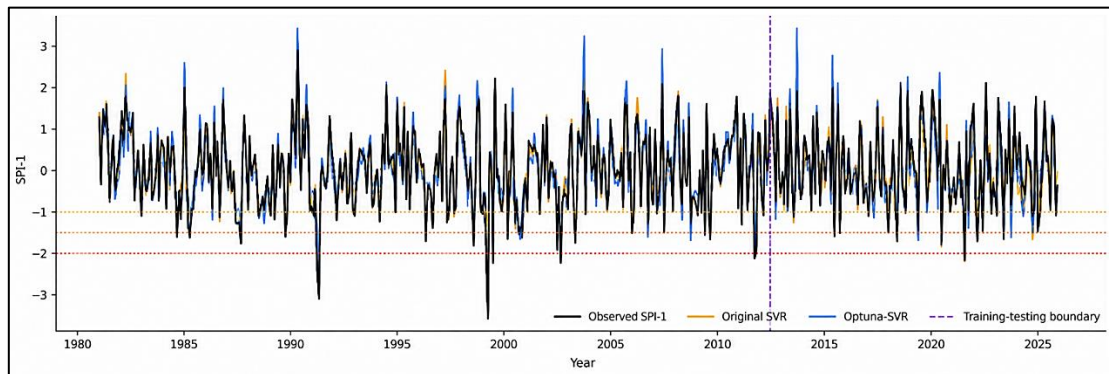


**Figure 6:** Observed and Estimated SPI-1 Across the Full Study Period for the Original SVR and Optuna-SVR, with the Training-testing Boundary Indicated

**Note:** SPI-1 = One-month Standardized Precipitation Index, SVR = Support Vector Regression. The vertical dashed line indicates the training-testing boundary.

Figure 6 compares observed and estimated SPI-1 across the complete record. The optimized model generally follows temporal variability more closely during the independent period while maintaining

stable behaviour across the split. Larger departures remain around several high-magnitude wet and dry observations, indicating residual difficulty at the tails of the distribution.

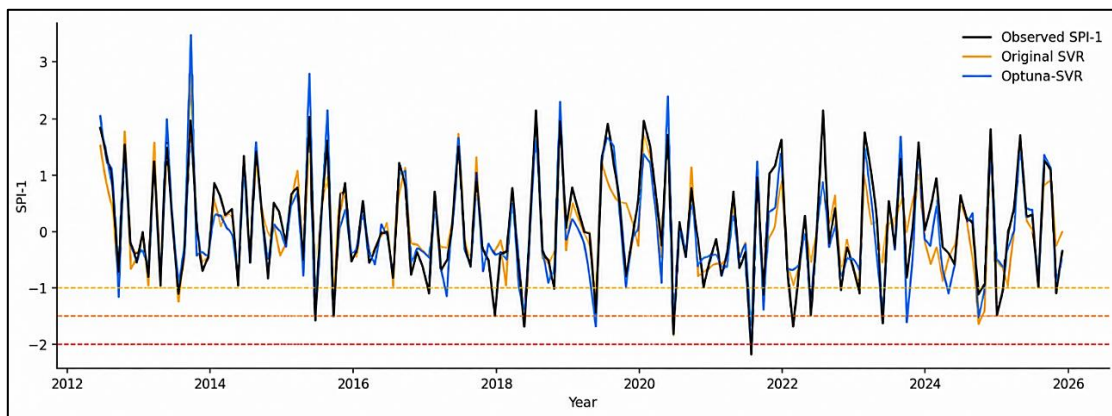


**Figure 7:** Training-period Observed and Estimated SPI-1 for the Original and Optimized SVR Models

**Note:** SPI-1 = One-month Standardized Precipitation Index; SVR = Support Vector Regression

Figure 7 provides a detailed comparison of observed and model-estimated SPI-1 for the period displayed. The optimized SVR generally tracks the direction and magnitude of monthly variability more consistently than the baseline

model. The remaining departures are concentrated around sharper peaks and troughs, which are more difficult for a smoothed regression response to reproduce.

Figure 8 focuses on independent testing behaviour and therefore provides the principal visual check of out-of-sample performance. Optuna-SVR reproduces most temporal fluctuations with

reduced error relative to the baseline. Nevertheless, some high-amplitude events remain underestimated or overestimated, consistent with the residual and category analyses.

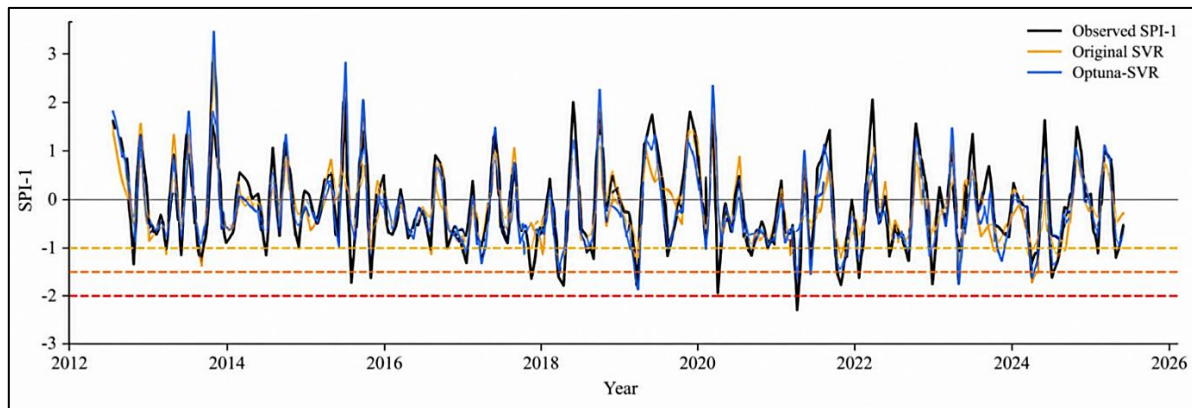


**Figure 8:** Independent Testing-period Observed and Estimated SPI-1 for the Original and Optimized SVR Models

**Note:** SPI-1 = One-month Standardized Precipitation Index; SVR = Support Vector Regression

### Magnitude of improvement after Bayesian optimization

Table 2 quantifies the change in test performance after Bayesian optimization. RMSE decreased by 15.15% and MAE by 12.93%, while  $R^2$  and NSE increased by 8.03%, correlation by 4.15% and the index of agreement by 2.72%. Absolute bias

increased slightly from 0.0532 to 0.0558, corresponding to a negative improvement value under the percentage convention used. Figure 9 provides a direct visual comparison of RMSE and MAE. The results therefore support improved overall accuracy and agreement, but not an improvement in every individual metric.

**Table 2:** Comparison of Testing Performance Metrics and Percentage Improvement of the Optuna-Optimized SVR Model Over the Baseline SVR

| Metric             | Original SVR | Optuna-SVR | Improvement (%) |
|--------------------|--------------|------------|-----------------|
| RMSE               | 0.4612       | 0.3914     | 15.15           |
| MAE                | 0.3470       | 0.3022     | 12.93           |
| $R^2$              | 0.7772       | 0.8396     | 8.03            |
| NSE                | 0.7772       | 0.8396     | 8.03            |
| Correlation        | 0.8837       | 0.9203     | 4.15            |
| Absolute Bias      | 0.0532       | 0.0558     | -4.96           |
| Index of Agreement | 0.9323       | 0.9577     | 2.72            |

**Note:** RMSE = Root Mean Square Error, MAE = Mean Absolute Error,  $R^2$  = coefficient of determination, NSE = Nash-sutcliffe Efficiency, SVR = Support Vector Regression. Positive improvement indicates better performance except for absolute bias, for which a smaller value is preferable

Figure 9 directly summarizes the reduction in error after Bayesian optimization. Both RMSE and MAE are lower for Optuna-SVR than for the original SVR, confirming improvement in average

and large-error behaviour. These reductions are consistent with the independent-test statistics reported in Table 2.

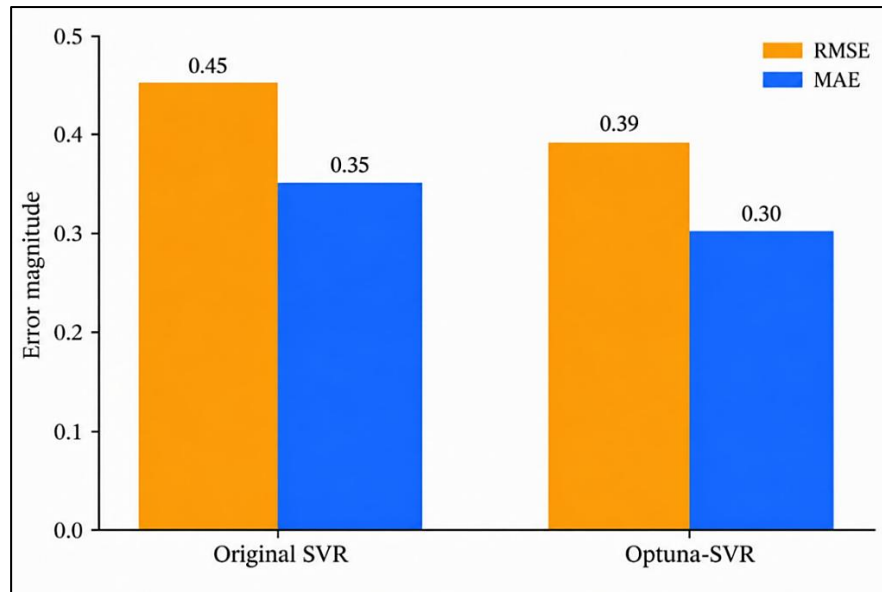


**Figure 9:** Testing RMSE and MAE Comparison Between Original SVR and Optuna-SVR

**Note:** RMSE = Root Mean Square Error, MAE = Mean Absolute Error, SVR = Support Vector Regression.

### Scatter and Residual Diagnostics

Figures 10 and 11 compare observed and estimated SPI-1 against the 1:1 reference line for the baseline and optimized models. Optuna-SVR shows tighter clustering around the reference line and a higher test correlation (0.920 versus 0.884). Figure 12 compares residuals over the testing

period, showing that errors are generally centered near zero but become larger for some high-magnitude observations. Figure 13 shows the residual distributions; the optimized model has a narrower distribution, consistent with its lower RMSE and MAE. Both models retain a small negative mean bias.

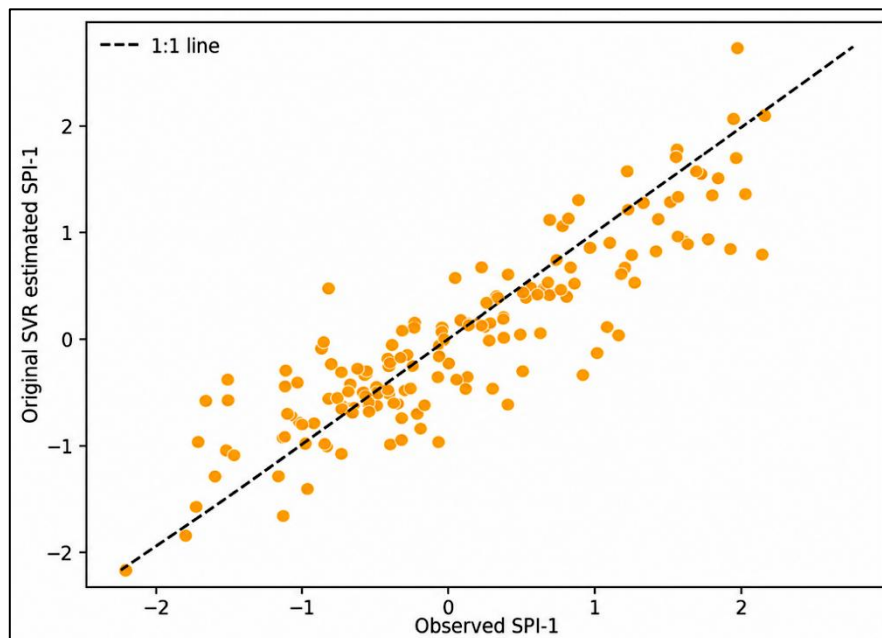


**Figure 10:** Observed Versus Estimated SPI-1 for the Original SVR During the Testing Period, Including the 1:1 Reference Line and Performance Statistics

**Note:** SPI-1 = One-month Standardized Precipitation Index; SVR = Support Vector Regression. The dashed 1:1 line represents perfect agreement.

Figure 10 shows the relationship between observed and baseline-SVR estimates during testing. Dispersion around the 1:1 line increases

toward some high-magnitude observations, indicating imperfect reproduction of extremes. The plot complements the aggregate metrics by

revealing both overall association and observation-specific deviations.

Figure 11 shows tighter clustering around the 1:1 line for Optuna-SVR than for the baseline model. This pattern is consistent with the higher test correlation and lower RMSE and MAE. Deviations remain at the largest positive and negative SPI values, emphasizing the need for caution when interpreting rare extremes.

Figure 12 indicates that residuals for both models are broadly distributed around zero, with larger errors occurring for selected high-magnitude estimates. The optimized model shows a more compact residual pattern over much of the fitted range. The small remaining asymmetry is consistent with the slight negative mean bias reported for the testing period.

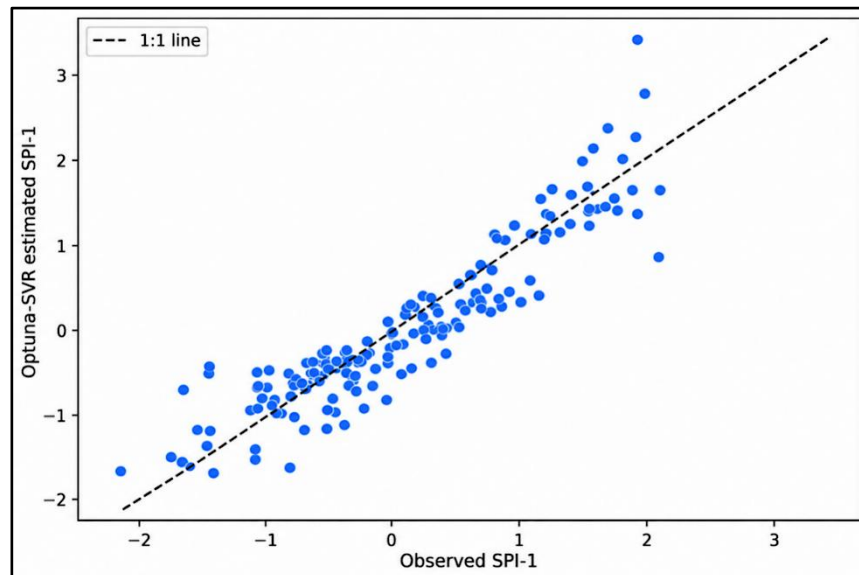


**Figure 11:** Observed Versus Estimated SPI-1 for Optuna-SVR During the Testing Period, Including the 1:1 Reference Line and Performance Statistics

**Note:** SPI-1 = One-month Standardized Precipitation Index, SVR = Support Vector Regression. The dashed 1:1 line represents perfect agreement.

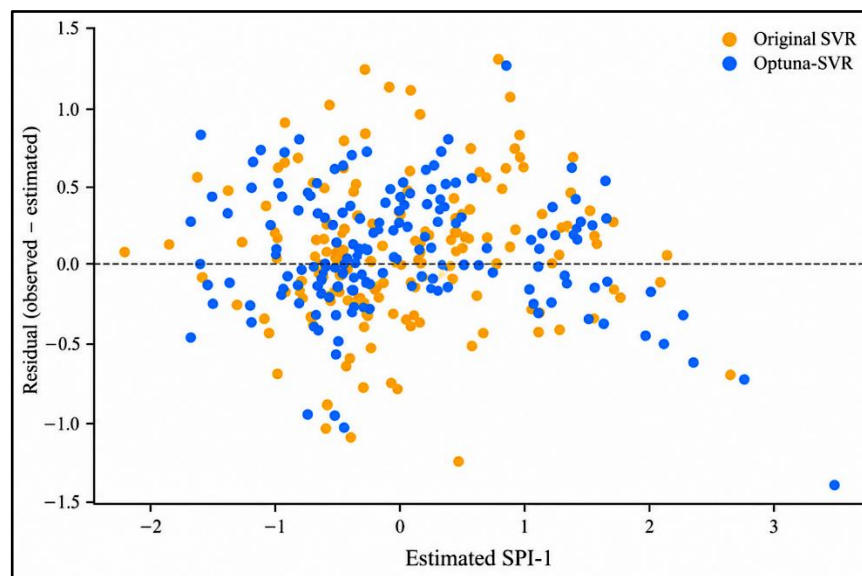


**Figure 12:** Residual Comparison for Original SVR and Optuna-SVR on the Independent Testing Period

**Note:** SVR = Support Vector Regression. Residuals are defined as observed minus estimated SPI-1.

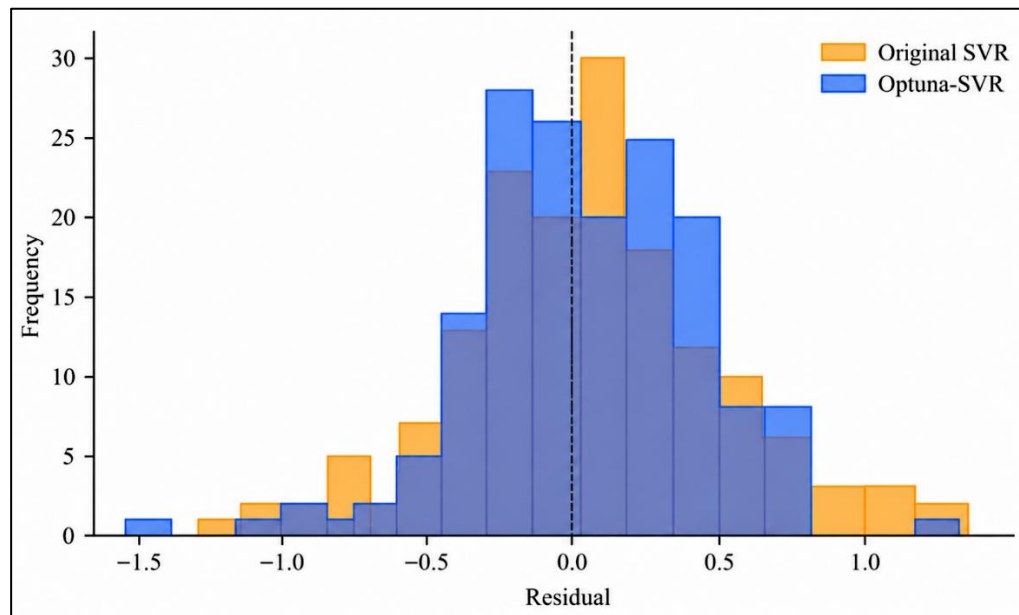


**Figure 13:** Distribution of Testing Residuals for the Original and Optimized SVR Models

**Note:** SVR = Support Vector Regression. The vertical dashed line denotes zero residual.

Figure 13 compares the testing residual distributions of the two models. The Optuna-SVR distribution is more concentrated near zero, in agreement with its lower RMSE and MAE. Both

distributions retain tail observations, showing that Bayesian optimization improves typical error behaviour without eliminating rare large residuals.

**Table 3:** Optimal Hyperparameter Values of the Optuna-optimized SVR Model

| Hyperparameter | Optimized value |
|----------------|-----------------|
| kernel         | rbf             |
| C              | 9706.42         |
| epsilon        | 0.389           |
| gamma          | 0.0019          |

**Note:** SVR = Support Vector Regression, rbf = Radial Basis Function, C = penalty parameter; epsilon = epsilon-insensitive-tube width, gamma = radial-basis-function kernel coefficient.

**Table 4:** Relative Importance of SVR Hyperparameters Estimated During Bayesian Optimization

| Hyperparameter | Relative importance |
|----------------|---------------------|
| gamma          | 0.509               |
| kernel         | 0.310               |
| C              | 0.108               |
| epsilon        | 0.073               |

**Note:** C = SVR penalty parameter, epsilon = epsilon-insensitive-tube width, gamma = radial-basis-function kernel coefficient. Relative importance values quantify contribution to the Optuna optimization objective.

### Optimized Hyperparameters and Optimization Behavior

Tables 3 and 4 report the selected hyperparameters and their relative importance. The optimum configuration used the RBF kernel with  $C = 9706.4209$ ,  $\epsilon = 0.3899069$  and  $\gamma = 0.0019159$ . Gamma had the highest relative importance [0.509], followed by kernel choice [0.310],  $C$  [0.108] and epsilon [0.073]. This ranking indicates that kernel geometry and response smoothness were more influential than fine adjustment of the epsilon tube.

The optimization history showed a progressive decrease in cross-validation RMSE, with the best configuration appearing at trial 81. This late improvement supports the use of a broad logarithmic search space: a small fixed grid centered on conventional values such as  $C = 1-100$  and  $\gamma = 0.01-1$  could have missed the selected combination of very large  $C$  and very small gamma.

### Predictor Importance

Table 5 and Figure 14 present permutation importance for the independent test set. Rainfall

was the dominant predictor (mean importance = 4.093), followed by Month\_sin [2.550] and Month\_cos [2.462]. Niño 3.4, DMI, PDO and SOI had much smaller mean importance values of 0.035, 0.026, 0.019 and 0.005, respectively. These results do not imply that teleconnections are climatologically unimportant; rather, once contemporaneous local rainfall and seasonality are known, the large-scale indices add comparatively little information for same-month SPI estimation.

Figure 14 confirms that contemporaneous rainfall is the dominant predictor of same-month SPI-1, followed by the two seasonal harmonic terms. The teleconnection indices provide much smaller incremental contributions once local rainfall and seasonality are known. The pattern supports interpreting the model as a drought-status estimator rather than evidence of direct causal dominance by the large-scale climate indices.

**Table 5:** Permutation Importance of Predictors in the Optuna-Optimized SVR Model

| Predictor | Mean permutation importance | Standard deviation |
|-----------|-----------------------------|--------------------|
| Rainfall  | 4.0932                      | 0.2289             |
| Month_sin | 2.5499                      | 0.1759             |
| Month_cos | 2.4623                      | 0.1428             |
| NINO34    | 0.0350                      | 0.0062             |
| DMI       | 0.0263                      | 0.0164             |
| PDO       | 0.0186                      | 0.0086             |
| SOI       | 0.0054                      | 0.0064             |

**Note:** NINO34 = Niño 3.4 sea-surface-temperature anomaly, DMI = Dipole Mode Index, PDO = Pacific Decadal Oscillation, SOI = Southern Oscillation Index. Larger mean permutation importance indicates greater deterioration in predictive performance when that predictor is permuted

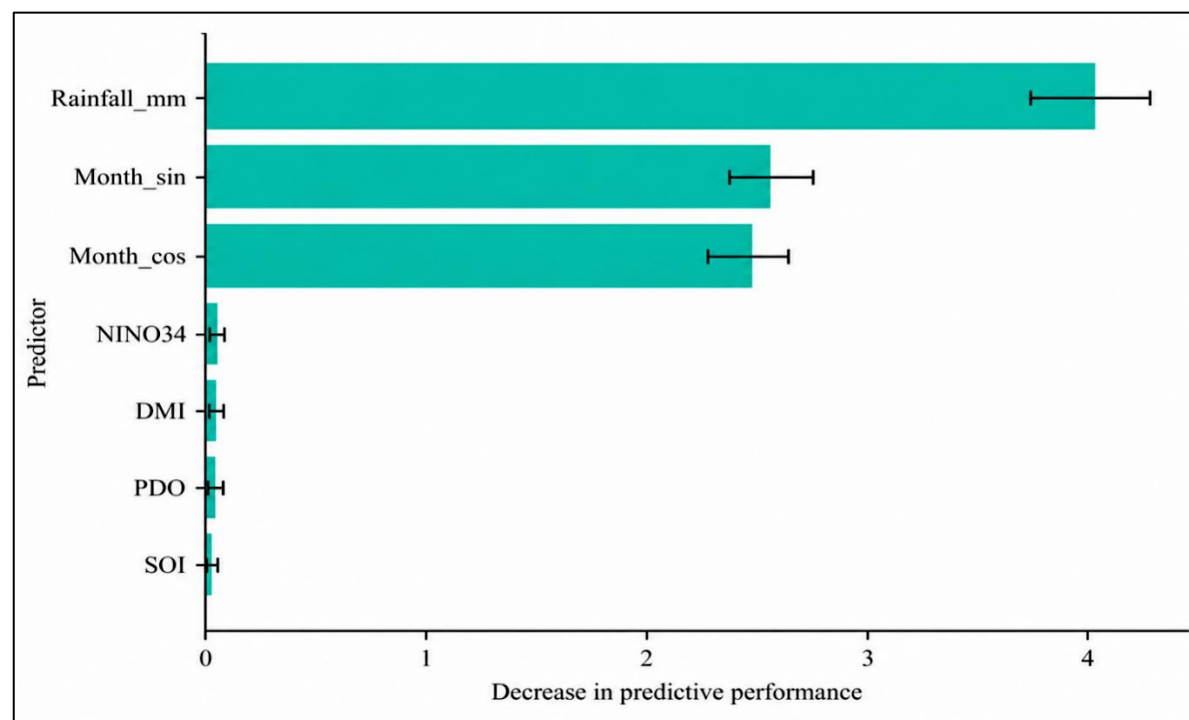


**Figure 14:** Permutation Feature Importance for the Optuna-SVR Model Based on the Independent Testing Set

**Note:** DMI = Dipole Mode Index, PDO = Pacific Decadal Oscillation, SOI = Southern Oscillation Index, NINO34 = Niño 3.4 sea-surface-temperature anomaly. Error bars represent variability across permutation repeats

## Drought-category Reproduction

Table 6 compares observed and model-estimated frequencies across SPI-1 categories. Of the test months, 109 were observed as near normal, 12 as moderately dry, eight as severely dry and one as extremely dry. The baseline model over-assigned the near-normal class (130 months) and underrepresented moderate and severe drought.

Optuna-SVR reduced the near-normal count to 115 and increased the estimated moderately and severely dry counts to nine and six. However, it did not identify the single observed extreme-drought month and overestimated some wet categories. The category analysis therefore confirms improved representation of common drought states while revealing the smoothing tendency of continuous regression for rare extremes.

**Table 6:** Observed and Model-estimated Frequencies of SPI-1 Wetness and Drought Categories During the Testing Period

| SPI category   | Observed | Original SVR | Optuna-SVR |
|----------------|----------|--------------|------------|
| Extremely Dry  | 1        | 1            | 0          |
| Severely Dry   | 8        | 3            | 6          |
| Moderately Dry | 12       | 7            | 9          |
| Near Normal    | 109      | 130          | 115        |
| Moderately Wet | 13       | 11           | 18         |
| Very Wet       | 16       | 7            | 8          |
| Extremely Wet  | 3        | 3            | 6          |

**Note:** SPI-1 = One-month Standardized Precipitation Index; SVR = Support Vector Regression. Values are counts of months in each observed or model-estimated wetness/drought category during the independent testing period

## Discussion

Bayesian optimization materially improved SVR generalization. The baseline model achieved a stronger training fit but a lower test  $R^2$ , whereas Optuna-SVR produced nearly identical training and testing efficiency. This pattern shows that the conventional parameter setting was more tightly fitted to historical fluctuations, while the optimized configuration provided a smoother response that transferred better to unseen observations. The result supports chronology-preserving model selection and independent testing rather than reliance on training accuracy alone (15). The selected hyperparameters are consistent with this generalization pattern. A very low gamma extends the influence of the RBF kernel across a broader region of feature space, reducing sensitivity to individual samples. The high C strongly penalizes errors outside the epsilon tube, whereas epsilon = 0.39 allows small deviations to remain unpenalized. Together, these settings balance smoothness and error control, which is consistent with the finding that gamma and kernel choice dominated hyperparameter importance.

Rainfall dominated predictor importance because SPI-1 is calculated directly from current-month precipitation. The high model accuracy therefore should not be interpreted as discovery of an independent physical predictor of drought. Instead, the model learned a nonlinear, seasonally

conditioned approximation to the rainfall-to-SPI transformation. Month<sub>sin</sub> and Month<sub>cos</sub> was also influential because an identical rainfall total can represent very different standardized anomalies during wet and dry seasons. Teleconnection indices contributed comparatively little after rainfall and seasonality were included. This is physically plausible because ENSO, IOD and PDO influence regional rainfall generation, while contemporaneous rainfall already contains the local realized effect of those large-scale processes (16-18). Their marginal importance is therefore reduced by mediated pathways and shared information. Teleconnections are likely to become more useful in a genuine lead-time design that excludes target-month rainfall and instead uses antecedent climate indices. The independent-test RMSE of 0.391 and MAE of 0.302 indicate good continuous SPI estimation. Nevertheless, category assignment remains sensitive near fixed thresholds: a small regression error can move an observation across the -1.0 or -1.5 boundary. This explains why drought-category reproduction was less accurate than the continuous metrics might suggest and why threshold-based operational use should retain uncertainty information.

The optimized model reduced the baseline tendency to classify too many months as near normal and improved representation of moderate and severe drought. Failure to reproduce the single

extreme-drought observation highlights the difficulty of learning rare events from a modest sample. Future work should evaluate weighted or quantile losses, carefully designed training-only augmentation, or two-stage models that first identify drought occurrence and then estimate severity. Such approaches must be validated without oversampling the test data or inflating apparent rare-event skill. The chronological 70:30 split is preferable to a random split for this hydroclimatic series because temporal dependence and possible non-stationarity can make randomly mixed samples unrealistically similar across training and testing sets. Expanding-window validation further restricted hyperparameter selection to past-to-future evaluation. However, a single final split remains sensitive to the chosen boundary, so rolling-origin assessment across multiple evaluation windows should be used in future work to quantify performance variability across climatic states (25).

NASA POWER enabled a complete and reproducible 45-year monthly record, but gridded precipitation should not be treated as error-free. Spatial averaging may damp local convective extremes and systematic product bias can propagate into SPI and model-performance estimates. Comparative work over India has documented such product-dependent biases (20). Future validation should therefore compare NASA POWER with gauge observations and alternative products such as CHIRPS and ERA5 (21, 22) and should quantify how input-product choice affects drought classification.

The modelling framework is best viewed as a supporting component of a real-time drought-monitoring system. Once monthly rainfall and climate indices are available, the optimized SVR can provide an automated estimate of prevailing SPI-1 status and a consistency check against conventionally calculated SPI. Agencies should nevertheless retain direct SPI computation as the authoritative, transparent benchmark because it is simpler and does not require model calibration. Accurate terminology is essential. Because target-month rainfall was used to estimate SPI for the same month, the analysis is not forward-looking forecasting. Describing it as forecasting would imply that the required precipitation was available before the target month. The appropriate terms are monthly drought-status estimation, drought

monitoring, or same-month SPI reconstruction. A true one- or multi-month forecast must use only information available at the issuance date, such as antecedent rainfall, lagged teleconnections, soil-moisture states, or seasonal climate predictions.

The results also illustrate that model complexity should match dataset size and study purpose. With 540 monthly observations, a calibrated kernel method provides a defensible nonlinear benchmark without the parameter burden of deep neural architectures. More complex models may be useful, but they should be compared on the same chronological holdout periods and should demonstrate added information beyond contemporaneous rainfall and seasonality (6, 10, 13). Operational deployment requires a predefined recalibration policy. Continuous monthly retuning may introduce instability and reduce reproducibility, whereas never updating the model may allow performance to degrade as climate or input products change. A practical approach is periodic recalibration, for example annually or after a defined number of new observations, combined with rolling-origin monitoring. Hyperparameter optimization need not be repeated every month; it can be triggered when monitoring identifies persistent performance deterioration or a substantive change in an input-data source.

From an implementation perspective, new monthly rainfall and climate-index data would be ingested, screened for missing or anomalous values, standardized using stored preprocessing parameters and passed through the optimized pipeline. The resulting SPI estimate should then be compared with directly calculated SPI and classified into drought categories. Large discrepancies can serve as a data-quality or model-drift flag. Versioned models, stored scaling parameters, fixed random states and reproducible code are necessary for auditability. The contrast between baseline and optimized training behaviour is informative. The baseline SVR had lower training error but higher testing error; Optuna selected hyperparameters by minimizing average validation error across temporally ordered folds rather than by minimizing in-sample loss. The optimized model therefore accepted a modest increase in training error to obtain more stable performance on unseen data, a desirable trade-off for nonstationary climate applications.

The resulting model accepted a slightly higher training error to achieve more stable and reliable performance on the testing data. For climate applications, where data are often nonstationary, this trade-off is preferable because it improves performance on unseen conditions instead of closely matching historical fluctuations that do not generalize well.

The performance comparison also demonstrates why multiple metrics are necessary. RMSE gives more weight to large errors, MAE represents average error magnitude,  $R^2$  and NSE quantify explanatory efficiency relative to a mean benchmark, correlation measures temporal co-variation, bias detects systematic over- or underestimation and the index of agreement summarizes overall correspondence. No single metric captures all aspects of drought-estimation quality. Most accuracy and agreement metrics improved after optimization, but absolute bias increased slightly. Reporting only  $R^2$  would therefore obscure an important trade-off. In drought monitoring, a model can have low mean bias yet still make threshold-crossing errors, while high correlation does not guarantee correct drought magnitude. Conclusions should accordingly be based on the joint pattern of metrics, category frequencies and residual diagnostics.

A further methodological issue is the distinction between statistical reconstruction and hydroclimatic causation. The predictors occupy different positions in the climate-drought pathway: SOI, Niño 3.4, DMI and PDO describe large-scale boundary conditions; rainfall is the local meteorological realization; and SPI is a standardized transformation of rainfall. Feature importance therefore represents conditional predictive contribution within the fitted model, not direct causal attribution.

## Conclusion

This study developed and independently evaluated a Bayesian-optimized SVR framework for monthly SPI-1 drought-status estimation at Kesinga in the Tel River Basin using NASA POWER rainfall, SOI, Niño 3.4, DMI, PDO and seasonal harmonics for January 1981-December 2025. The 540-month record was divided chronologically into 70% training and 30% independent testing, with scaling and hyperparameter optimization restricted to

temporally valid training pipelines. The baseline SVR achieved test RMSE = 0.461, MAE = 0.347,  $R^2$  = NSE = 0.777, correlation = 0.884, bias = -0.053 and index of agreement = 0.932, whereas Optuna-SVR reduced RMSE to 0.391 and MAE to 0.302 and increased  $R^2$  and NSE to 0.840, correlation to 0.920 and index of agreement to 0.958. Thus, Bayesian optimization improved out-of-sample accuracy and stability while accepting a weaker in-sample fit.

The principal contribution is a transparent, chronology-preserving benchmark that combines systematic SVR tuning with explicit interpretation of predictor importance, residual behaviour and drought-category reproduction. Rainfall and seasonal harmonics were the dominant contributors to same-month SPI-1 estimation, whereas the teleconnection indices added comparatively little information after contemporaneous rainfall was known. The practical consequence is that the framework can support automated monthly drought monitoring and data-quality cross-checking, but it should complement rather than replace direct SPI calculation and should not be described as advance forecasting.

The findings also have operational limits. The analysis is based on one station, one precipitation product, one final chronological holdout and a relatively small number of extreme drought observations. The optimized model did not reproduce the rarest extreme event reliably and point-error metrics do not quantify predictive uncertainty near drought-category thresholds. These limitations restrict direct basin-wide generalization and indicate that high-impact drought declarations should not rely on the machine-learning estimate alone.

Future research should extend the framework to multiple Tel Basin stations; compare NASA POWER with gauges, CHIRPS and ERA5; evaluate SPI-3, SPI-6 and SPI-12; quantify predictive uncertainty; repeat optimization across multiple seeds; and use rolling-origin evaluation across multiple climatic windows. Genuine forecasting should exclude target-month rainfall and use only antecedent rainfall, lagged teleconnections, soil-moisture states, or seasonal climate predictions available at the forecast issuance date. These extensions would test whether the approach retains skill under

spatial heterogeneity, climate nonstationarity and explicit lead-time conditions.

## Abbreviations

DMI: Dipole Mode Index, MAE: Mean Absolute Error, NSE: Nash-Sutcliffe Efficiency, PDO: Pacific Decadal Oscillation, RBF: Radial Basis Function, RMSE: Root Mean Square Error, SOI: Southern Oscillation Index, SPEI: Standardized Precipitation Evapotranspiration Index, SPI: Standardized Precipitation Index, SVR: Support Vector Regression

## Acknowledgement

The authors sincerely appreciate the support of Centurion University of Technology and Management for providing laboratory facilities.

## Author Contributions

Abhisek Kar: Conceptualization, Methodology, Investigation, Data Curation, Formal Analysis, Visualization, Writing - Original Draft, Sujata Chakravarty: Conceptualization, Supervision, Validation, Project Administration, Writing - Review and Editing, Bibhuti Bhusan Sahoo: Methodology, Validation, Formal Analysis, Writing - Review and editing. All authors have read and approved the final version of the manuscript.

## Conflict of Interest

The authors declare that they have no competing financial interests or personal relationships that could have influenced the work reported in this study.

## Data Availability

NASA POWER rainfall data are publicly available through the NASA POWER Data Access Viewer. The processed dataset, modelling notebook, optimization results, prediction outputs and publication figures will be deposited in a public repository upon acceptance. Analyses were conducted in Python using pandas, NumPy, scikit-learn, Optuna, SciPy and Matplotlib; the reproducible Google Colab code can be found here [https://github.com/bibhuatGitHUB/SPI-Prediction/blob/main/Complete\\_Baseline\\_and\\_Optimized\\_SVR\\_SPI\\_Analysis%20\(1\).ipynb](https://github.com/bibhuatGitHUB/SPI-Prediction/blob/main/Complete_Baseline_and_Optimized_SVR_SPI_Analysis%20(1).ipynb).

## Declaration of Artificial Intelligence (AI) Assistance

The authors acknowledge the use of generative AI to assist in the paraphrasing of certain parts of the

manuscript. All content generated through AI was critically reviewed, edited and verified by the authors to ensure accuracy, originality and compliance with academic standards. The authors take full responsibility for the integrity and validity of the manuscript.

## Ethics Approval

Not applicable.

## Funding

None.

## References

- Guttman NB. Comparing the Palmer Drought Index and the Standardized Precipitation Index. *J Am Water Resour Assoc.* 1998;34(1):113-121. doi:10.1111/j.1752-1688.1998.tb05964.x
- Guttman NB. Accepting the Standardized Precipitation Index: a calculation algorithm. *J Am Water Resour Assoc.* 1999;35(2):311-322. doi:10.1111/j.1752-1688.1999.tb03592.x
- Šebenik U, Brilly M, Šraj M. Drought analysis using the Standardized Precipitation Index (SPI). *Acta Geogr Slov.* 2017;57(1):31-49. doi:10.3986/AGS.729
- Mishra SS, Nagarajan R. Spatio-temporal drought assessment in Tel River basin using Standardized Precipitation Index (SPI) and GIS. *Geomat Nat Hazards Risk.* 2011;2(1):79-93. doi:10.1080/19475705.2010.533703
- Vicente-Serrano SM, Beguería S, López-Moreno JI. A multiscalar drought index sensitive to global warming: the Standardized Precipitation Evapotranspiration Index. *J Clim.* 2010;23(7):1696-1718. doi:10.1175/2009JCLI2909.1
- Dikshit A, Pradhan B, Huete A. An improved SPEI drought forecasting approach using the long short-term memory neural network. *J Environ Manage.* 2021;283:111979. doi:10.1016/j.jenvman.2021.111979
- Felsche E, Ludwig R. Applying machine learning for drought prediction in a perfect model framework using data from a large ensemble of climate simulations. *Nat Hazards Earth Syst Sci.* 2021;21(12):3679-3691. doi:10.5194/nhess-21-3679-2021
- Li X, Jia H, Wang L. Remote sensing monitoring of drought in Southwest China using random forest and eXtreme gradient boosting methods. *Remote Sens.* 2023;15(19):4840. doi:10.3390/rs15194840
- Smola AJ, Schölkopf B. A tutorial on support vector regression. *Stat Comput.* 2004;14(3):199-222. doi:10.1023/B:STCO.0000035301.49549.88
- Belayneh A, Adamowski J. Standard precipitation index drought forecasting using neural networks, wavelet neural networks and support vector regression. *Appl Comput Intell Soft Comput.* 2012;794061. doi:10.1155/2012/794061
- Mirboluki A, Mehraein M, Kisi O. Improving accuracy of neuro-fuzzy and support vector regression for

- drought modelling using grey wolf optimization. *Hydrol Sci J*. 2022;67(10):1582-1597. doi:10.1080/02626667.2022.2082877
12. Belayneh A, Adamowski J, Khalil B. Short-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet transforms and machine learning methods. *Sustain Water Resour Manag*. 2016;2(1):87-101. doi:10.1007/s40899-015-0040-5
  13. Belayneh A, Adamowski J, Khalil B, Ozga-Zielinski B. Long-term SPI drought forecasting in the Awash River Basin in Ethiopia using wavelet neural network and wavelet support vector regression models. *J Hydrol*. 2014;508:418-429. doi:10.1016/j.jhydrol.2013.10.052
  14. Munshi RM, Munshi LR, Himdi H, *et al.* Optimising hyperparameters with a tree structured Parzen estimator to improve diabetes prediction. *Sci Rep*. 2025;15:35430. doi:10.1038/s41598-025-19295-x.
  15. Bischl B, Binder M, Lang M, Pielok T, Richter J, Coors S, Thomas J, Ullmann T, Becker M, Boulesteix A-L, Deng D, Lindauer M. Hyperparameter optimization: foundations, algorithms, best practices and open challenges. *WIREs Data Min Knowl Discov*. 2023;13(2):e1484. doi:10.1002/widm.1484
  16. Chattopadhyay R, Rao SA, Sabeerali CT, George G, Rao DN, Dhakate A, Salunke K. Large scale teleconnection patterns of Indian summer monsoon as revealed by CFSv2 retrospective seasonal forecast runs. *Int J Climatol*. 2016;36(9):3297-3313. doi:10.1002/joc.4556
  17. Joseph S, Sahai AK, Chattopadhyay R, Goswami BN. Can El Niño-Southern Oscillation events modulate intraseasonal oscillations of Indian summer monsoon? *J Geophys Res Atmos*. 2011;116(D20):D20123. doi:10.1029/2010JD015510
  18. Gupta A, Pandey AC, Mitra AK. Impact of atmospheric response of ENSO and IOD on boreal summer rainfall variability over the Indian Ocean in coupled models. *Clim Dyn*. 2023;61(9-10):4107-4124. doi:10.1007/s00382-023-06796-6
  19. Khalid MR, Ahmed S, Abdullah A. Assessing NASA-POWER precipitation product in predicting surface flow: Lower Jhelum River case study. *Air Soil Water Res*. 2024;17. doi:10.1177/11786221241280753
  20. Dubey S, Gupta H, Goyal MK, Joshi N. Evaluation of precipitation datasets available on Google Earth Engine over India. *Int J Climatol*. 2021;41(10):4844-4863. doi:10.1002/joc.7102
  21. Hersbach H, Bell B, Berrisford P, *et al.* The ERA5 global reanalysis. *Q J R Meteorol Soc*. 2020;146(730):1999-2049. doi:10.1002/qj.3803
  22. Funk C, Peterson P, Landsfeld M, Pedreros D, Verdin J, Shukla S, Husak G, Rowland J, Harrison L, Hoell A, Michaelsen J. The climate hazards infrared precipitation with stations-a new environmental record for monitoring extremes. *Sci Data*. 2015;2:150066. doi:10.1038/sdata.2015.66
  23. Das J, Jha S, Goyal MK. On the relationship of climatic and monsoon teleconnections with monthly precipitation over meteorologically homogeneous regions in India: wavelet and global coherence approaches. *Atmos Res*. 2020;238:104889. doi:10.1016/j.atmosres.2020.104889
  24. Belayneh A, Adamowski J, Khalil B, Quilty J. Coupling machine learning methods with wavelet transforms and the bootstrap and boosting ensemble approaches for drought prediction. *Atmos Res*. 2016;172-173:37-47. doi:10.1016/j.atmosres.2015.12.017
  25. Bergmeir C, Hyndman RJ, Koo B. A note on the validity of cross-validation for evaluating autoregressive time series prediction. *Comput Stat Data Anal*. 2018;120:70-83. doi:10.1016/j.csda.2017.11.003

**How to Cite:** Kar A, Chakravarty S, Sahoo BB. Bayesian-optimized Support Vector Regression for Monthly Drought Estimation Using Rainfall and Large-scale Climate Teleconnections. *Int Res J Multidiscip Scope*. 2026;7(4):1752-1770. DOI: 10.47857/irjms.2026.v07i04.013824