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Multi-Variable Agrometeorological Parameter Combination for Drought Early Warning System Using Hybrid SSA–AMBP Algorithm

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Abstract: Drought is one of the hydrometeorological disasters that has a significant impact on the agricultural sector, water availability, and food security, thus requiring an accurate and adaptive early warning system. This study aims to develop and evaluate a drought Early Warning System (EWS) model based on a combination of multi-variable agrometeorological parameters using a hybrid approach of Singular Spectrum Analysis (SSA) and Adaptive Model-Based Prediction (AMBP). The agrometeorological data used includes rainfall, air temperature, humidity, solar radiation, wind speed, and other supporting variables processed in the form of monthly time series over a period of ten years. The SSA method is used to perform signal denoising and extract dominant components from the data, while AMBP is applied as an adaptive predictive model to generate SPI-6 drought index forecasts. Model performance is evaluated using RMSE and the coefficient of determination (R^2) in the model training and evaluation phases. The results show that the hybrid SSA–AMBP model has the best performance compared to single methods, with an RMSE value of 0.149 and R^2 of 0.983 in the model training phase, and an RMSE of 0.176 and R^2 of 0.941 in the model evaluation phase. In addition, the 2026 prediction results show a seasonal pattern with indications of a moderate dry period from October to November. These findings indicate that the developed model demonstrates relatively high predictive accuracy and stability based on RMSE and R^2 evaluation metrics within the SPI-6 dataset used in this study, and it has the potential to serve as a conceptual basis for decision-support in drought risk mitigation, water resource management, and sustainable agricultural planning.

Keywords: drought; early warning system; singular spectrum analysis; adaptive model-based prediction; agrometeorological parameters

INTRODUCTION

Drought is one of the most significant threats to the agricultural sector due to its close link to climate change and increasingly erratic weather variability. In the last two decades, the frequency and intensity of droughts have reportedly increased significantly, causing serious disruption to food crop productivity and groundwater availability. This phenomenon is exacerbated by rainfall anomalies, changing seasonal patterns, and rising air temperatures that affect plant growth cycles (Zubair et al., 2025). The impact is not only felt by farmers, but also affects the entire food supply chain. The complexity of this problem requires a more accurate scientific approach to monitoring hydrometeorological conditions, making drought modeling an important part of agricultural risk mitigation efforts (Harsanto et al., 2025).

Global reports indicate that the frequency of droughts has increased by approximately 25–30% since 2000, with longer durations and more extreme intensity (Miralles et al., 2025). In Southeast Asia, annual rainfall anomalies have decreased by an average of 8–15% during the dry season, while air temperatures have increased by approximately 0.3–0.6°C per decade (Sentian et al., 2022). The direct impact is evident in the decline in food crop productivity, which reaches 10–25% in drought-prone areas, as well as a decrease in groundwater discharge of up to 15–30% during prolonged dry seasons. This data confirms that drought is no longer an incidental occurrence, but has become a systemic phenomenon that requires a precise monitoring and prediction system

*name of corresponding author

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(Mariyanto and Muda, 2025; Silamat et al., 2024). Given the magnitude of potential losses, the need for an early warning system (EWS) for drought is becoming increasingly urgent. In this study, the term EWS refers operationally to a predictive modeling framework designed to provide early drought risk information as a decision-support tool, rather than a fully deployed real-time monitoring system. Therefore, the proposed system should be interpreted as a conceptual predictive framework rather than a fully operational real-time early warning system, since it has not yet undergone field deployment or operational validation. An effective EWS must be able to detect environmental changes early and provide predictive information before extreme conditions occur. Such a system requires the integration of rich and representative agrometeorological data on field conditions (Elisa et al., 2025). Parameters such as rainfall, air temperature, humidity, solar radiation, and evapotranspiration are key indicators in understanding the dynamics of water availability. The use of more comprehensive parameters provides a solid basis for the development of adaptive and realistic prediction models (Wang et al., 2025).

A multi-variable agrometeorological data-based approach provides a more comprehensive picture than a single-variable approach. Interactions between climate variables reflect complex biophysical processes, especially in the context of drought, which is influenced by many factors simultaneously. However, challenges arise when data patterns are non-linear, fluctuating, and contain high levels of noise (Satapathy & Dietrich, 2024). Conventional models are often unable to capture this complexity, resulting in reduced prediction accuracy, especially under extreme conditions. Therefore, an analysis method is needed that can reduce noise while maintaining the main signal structure (Lalika et al., 2024).

Various drought modeling studies still rely heavily on single parameters such as rainfall or a specific drought index. This approach is relatively simple, but it is less stable because it does not represent all the climate variability that affects land conditions. Quantitatively, several studies report Root Mean Square Error (RMSE) prediction error values ranging from 12–25% and coefficient of determination (R^2) values only in the range of 0.55–0.72, especially during periods of extreme climate. In addition, delays in early detection of drought events were reported to reach 1–3 weeks compared to actual conditions (Xiao et al., 2024). This limitation indicates that research integrating more than two parameters is still relatively limited, making the need for stronger multi-variable models increasingly important (Sukoharjo, 2023).

In addition to parameter limitations, the lack of advanced methods capable of optimally processing multi-variable time series is also a problem in itself. Singular Spectrum Analysis (SSA) has the ability to decompose signals so that the main patterns can be maintained, while noise can be significantly reduced (Lenczuk et al., 2024). On the other hand, Adaptive Model-Based Prediction (AMBP) excels at learning dynamically changing short-term patterns (Reddy et al., 2025). Recent studies show that signal decomposition-based approaches can reduce noise levels by 30–50%, while adaptive models can improve prediction accuracy by 15–30% compared to single models. However, the integration of SSA and AMBP in drought modeling is still very limited, creating a relevant and strategic research gap (Base et al., 2025).

Based on this research gap, the development of a model that combines multi-variable agrometeorological parameters with a hybrid SSA–AMBP approach is an important scientific contribution. This integration is expected to optimize the strength of SSA in signal management and the advantages of AMBP in pattern adaptation (Gupta et al., 2024). The hybrid approach has the potential to produce drought predictions that are more stable, responsive to environmental changes, and resistant to data fluctuations (Ahire et al., 2025). In addition, the use of multi-variable parameters improves the representation of hydrometeorological conditions in a more realistic manner, thereby strengthening the quality of predictive information (Houmma et al., 2023;Yuan et al. 2025).

This study aims to develop and evaluate a drought Early Warning System model based on a combination of multi-variable agrometeorological parameters using a hybrid SSA–AMBP approach. This study is expected to improve the accuracy of drought predictions and strengthen the model's ability to adapt to changing climate patterns. In addition, the resulting model is expected to serve as a basis for decision-making in the agricultural sector, particularly in drought risk mitigation, water resource management, and sustainable crop planning.

METHOD

This study uses an experimental quantitative approach that aims to develop a drought prediction model based on multivariable agrometeorological parameters. The data used is satellite-based observational data obtained from the National Aeronautics and Space Administration (NASA) at coordinates latitude −8.54279 and longitude 118.69280. The data analyzed is monthly data for a ten-year observation period, obtained through statistical aggregation of daily data. The transformation of daily data into monthly data was carried out to reduce short-term random fluctuations and strengthen seasonal patterns relevant to drought analysis. The variables used in this study include rainfall, solar radiation, surface and root zone soil moisture, air humidity, average, minimum, and maximum air temperatures, daily temperature range, and average, minimum, and maximum wind speeds.

The main indicator of drought conditions in this study is the Standardized Precipitation Index (SPI), which is calculated based on monthly rainfall data. For a time scale of k months, rainfall accumulatic … ormulated as

(1)

*name of corresponding author

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$$P_t^{(k)} = \sum_{i=0}^{k-1} P_{t-i}$$

where $P_t^{(k)}$ denotes the cumulative rainfall at time t for a k-month scale, P_{t-i} represents rainfall during the previous period, t is the observation time index, k indicates the accumulation time scale, and i is the summation index.

Rainfall distribution is assumed to follow a Gamma distribution expressed as

$$f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta} \tag{2}$$

where $f(x)$ is the probability density function, x represents the observed rainfall value, α is the shape parameter, β is the scale parameter, and Γ(α) e denotes the Gamma function.

The SPI value is obtained by transforming the cumulative probability into a standard normal distribution as

$$\mathrm{SPI} = \Phi^{-1}\big(G(x)\big) \tag{3}$$

where **SPI A value that indicates the level of dryness or wetness of an area**, *G(x)* denotes the cumulative distribution function of the Gamma distribution and, Φ^{-1} represents the inverse standard normal function, which is used to transform probability values into standard values (z-scores).

The data preprocessing stage includes handling missing values using time series interpolation and data normalization to equalize the scale between variables. Next, the SSA method is applied, beginning with the embedding stage, which forms a trajectory (Hankel) matrix from the time series, $X = (x_1, x_2, \dots, x_N)$. The embedding process transforms the original time series into a trajectory matrix as expressed in (4)

$$\begin{bmatrix} X_1 & X_2 & \cdots & X_K \\ X_2 & X_3 & \cdots & X_{K+1} \\ \vdots & & \ddots & \vdots \\ X_L & X_{L+1} & \cdots & X_N \end{bmatrix} \tag{4}$$

where *X* denotes the trajectory matrix constructed from the original time series, *L* Window represents the window length, and *K* = *N* - *L* + 1 indicates the number of columns. The window length L was determined empirically based on the rule *L* < *N/2* to ensure adequate separation between trend and noise components, while the number of reconstructed components r was selected based on the cumulative contribution of singular values to preserve dominant signal variance.

The trajectory matrix is then decomposed using Singular Value Decomposition (SVD) as expressed in (5)

$$X = U\Sigma V^T \tag{5}$$

where X denotes the trajectory (Hankel) matrix obtained from the time series transformation, U represents the matrix of left singular vectors describing the principal patterns in the row direction, Σ is a diagonal matrix containing singular values that measure the contribution of each component to the total data variance, and V^T is the transpose of the right singular vector matrix representing the principal patterns in the column direction of the data.

The reconstructed time series using the first r components is expressed as

$$X^{(r)} = \sum_{i=1}^{r} \sigma_i u_i v_i^T \tag{6}$$

where $X^{(r)}$ denotes the reconstructed matrix obtained after selecting r principal components, r represents the number of singular components used in the reconstruction process, σ_i is the i-th singular value indicating the contribution magnitude of each component to the data variance, u_i is the i-th left singular vector describing the dominant pattern in the row direction, and v_i^T is the transpose of the i-th right singular vector representing the dominant pattern in the column direction of the data.

*name of corresponding author

The reconstructed SSA time series is subsequently used as input for Adaptive Model-Based Prediction (AMBP) to perform forecasting. In the hybrid framework, the final prediction is generated through an adaptive ensemble learning mechanism. In this study, AMBP employs an adaptive regression ensemble consisting of Ridge Regression, Random Forest, and Gradient Boosting, where model selection and parameter updating are dynamically performed based on prediction error minimization during the training process.

$$\widehat{y_{Hybrid}} = AMBP\big(SSA(X)\big) \tag{7}$$

where $\widehat{y_{Hybrid}}$ is the final prediction value generated by the hybrid SSA–AMBP model, *X* denotes the original time series input data, *SSA(X)* represents the processed signal obtained from SSA, and, $AMBP(\cdot)$: denotes the AMBP model used to perform forecasting based on the SSA output data.

Model performance evaluation was conducted using a temporal data splitting approach to preserve the chronological characteristics of the time series. The dataset consisted of 252 monthly observations, which were divided into training and testing subsets using an 80%–20% ratio. The first 202 observations (80%) were used for model training, while the remaining 50 observations (20%) were reserved for model testing to evaluate the out-of-sample predictive performance of the proposed model.. This division aims to avoid information leakage between the training and testing phases. The prediction accuracy level is assessed using several statistical metrics, namely Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Among these metrics, RMSE and R^2 are treated as the primary evaluation indicators, while MSE and MAE are used as supporting metrics to provide complementary error analysis.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i\right)^2 \tag{8}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{9}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{10}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{11}$$

Through this stage, the hybrid SSA–AMBP model is expected to produce accurate, stable, and adaptive drought predictions as a basis for developing a multi-variable agrometeorological parameter-based early warning system for drought.

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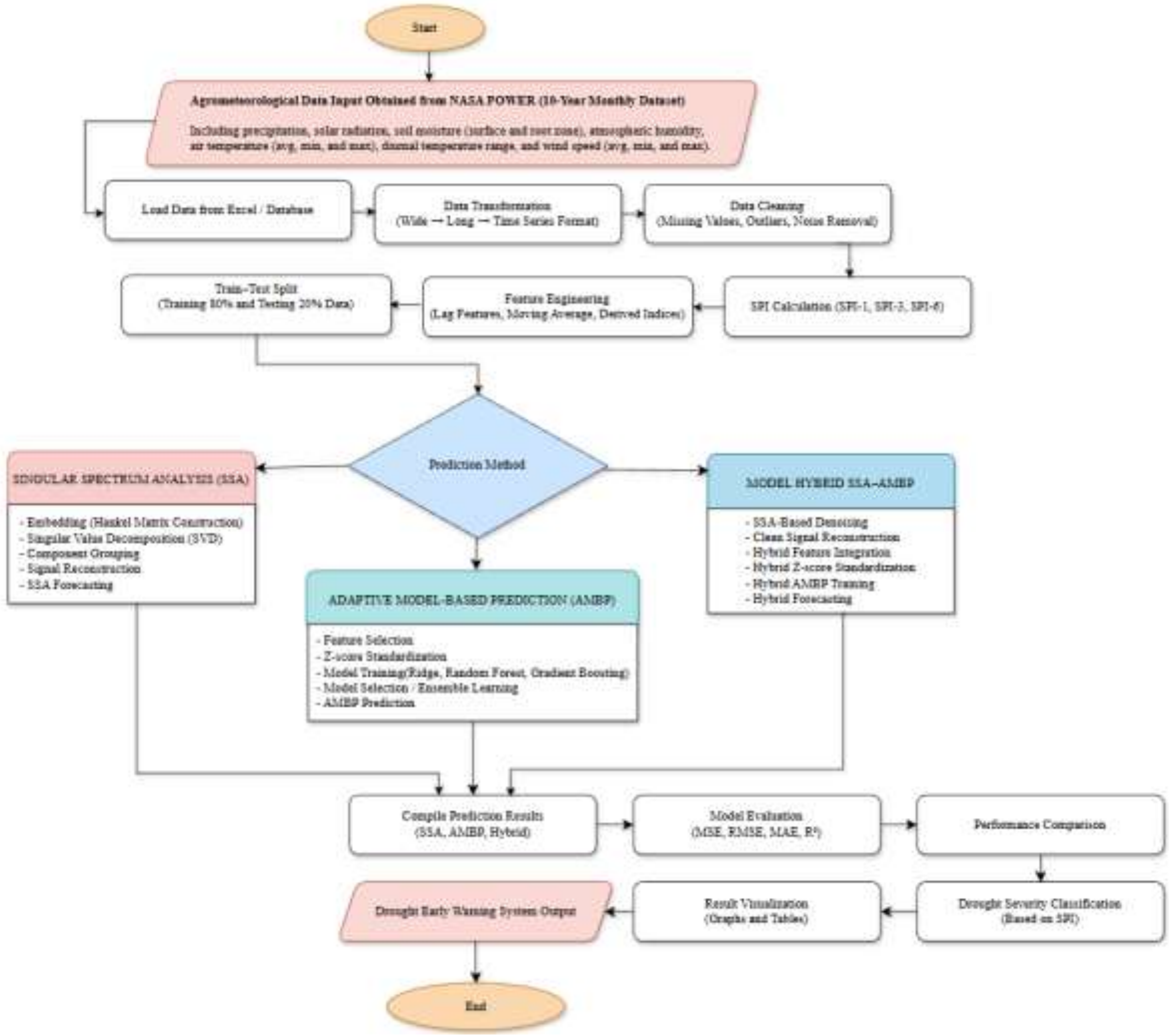

Fig. 1 Research flow

Fig. 1 shows the research flow of the drought prediction and early warning system based on a combination of agrometeorological parameters using the hybrid SSA–AMBP approach. The process begins with the collection of agrometeorological data from the NASA POWER database for a ten-year period on a monthly basis, covering variables such as rainfall, solar radiation, soil moisture, air humidity, air temperature, daily temperature range, and wind speed. The obtained data is then loaded from the storage source and converted to a time series format for temporal analysis. The preprocessing stage is carried out through a data cleaning process, which includes handling missing values, detecting outliers, and reducing noise. After that, the data was divided into training data and test data with a ratio of 80% and 20%. The next process involved feature engineering, such as lag feature formation, moving averages, and derivative indices, as well as calculating the SPI drought index on the SPI-1, SPI-3, and SPI-6 time scales as the main variables in modeling.

At the modeling stage, the system applies three prediction approaches, namely SSA, AMBP, and the hybrid SSA–AMBP model. The SSA method is used to perform embedding through Hankel matrix construction, singular value decomposition, component clustering, and signal reconstruction to extract dominant patterns and reduce noise. Meanwhile, the AMBP method focuses on feature selection, data standardization, regression-based model training and machine learning, and ensemble model formation. The hybrid model integrates the results of SSA processing with the AMBP prediction mechanism to improve forecasting quality. All prediction results are then compiled and evaluated using performance metrics, such as MSE, RMSE, MAE, and R^2, and compared to determine the best model. The final stage involves visualizing the results in graphs and tables, classifying the severity of drought based on SPI values, and presenting the early warning system output as a basis for decision-making in agriculture and water resource management.

*name of corresponding author

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RESULT

Performance evaluation of the model during the model training phase aims to assess the ability of the SSA, AMBP, and hybrid SSA–AMBP methods to learn and represent SPI-6 drought index patterns optimally. The assessment process was carried out using several statistical indicators, including MSE, RMSE, MAE, and R^2. In general, smaller error values in MSE, RMSE, and MAE reflect a higher level of prediction accuracy, while an R^2 value close to one indicates a better ability of the model to explain the variation in actual data. Through these evaluation results, the effectiveness of each method in capturing the characteristics of SPI-6 data in the training phase can be identified, which also serves as a basis for determining the most suitable model to be used in the model evaluation phase. The results of the training model evaluation are shown in Table 1, and the results of the testing model evaluation are shown in Table 2.

Table 1
Training Model Evaluation

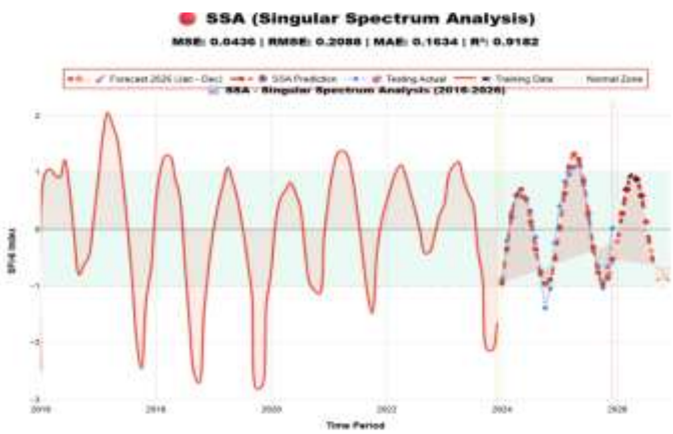
Algorithm	DATA	MSE	RMSE	MAE	R^2
SSA	SPI-6	0.105	0.324	0.234	0.921
AMBP	SPI-6	0.061	0.248	0.185	0.954
Hybrid SSA-AMBP	SPI-6	0.022	0.149	0.103	0.983

Table 1 shows that the lowest MSE value is 0.022, RMSE is 0.149, and MAE is 0.103, indicating the smallest prediction error and higher model accuracy. The superiority of the hybrid SSA–AMBP model is also reinforced by the highest R^2 value of 0.983, which indicates that approximately 98.3% of the SPI-6 data variation in the model training phase can be explained by the model. Meanwhile, the AMBP method showed better performance than SSA, with lower MSE, RMSE, and MAE values and a higher R^2, but still below the performance of the hybrid model. Overall, these evaluation results confirm that the integration of SSA for signal denoising and dominant component extraction with AMBP as an adaptive predictive model can improve the accuracy and reliability of SPI-6 drought index modeling in the model training phase.

Table 2
Testing Model Evaluation

Algorithm	DATA	MSE	RMSE	MAE	R^2
SSA	SPI-6	0.436	0.208	0.163	0.918
AMBP	SPI-6	0.042	0.206	0.169	0.920
Hybrid SSA-AMBP	SPI-6	0.030	0.176	0.152	0.941

Table 2 shows that the SSA method independently produces an MSE value of 0.436 and an RMSE of 0.208 with an R^2 of 0.918, which indicates that the model's ability to capture general data patterns is quite good, but still has a relatively high level of absolute error. The AMBP method shows improved performance compared to SSA with a significant decrease in the MSE value to 0.042 and an increase in the R^2 value to 0.920, although the RMSE and MAE values are relatively close to SSA. Meanwhile, the hybrid SSA–AMBP model provided the best performance among the three, as indicated by the lowest MSE, RMSE, and MAE values, at 0.030, 0.176, and 0.152, respectively, and the highest R^2 value of 0.941. The decrease in error values and increase in the coefficient of determination in this hybrid model indicate that the integration of SSA in reducing noise and extracting dominant patterns, which are then predicted using adaptive AMBP, can significantly improve the accuracy and stability of SPI-6 predictions compared to the use of each method separately.



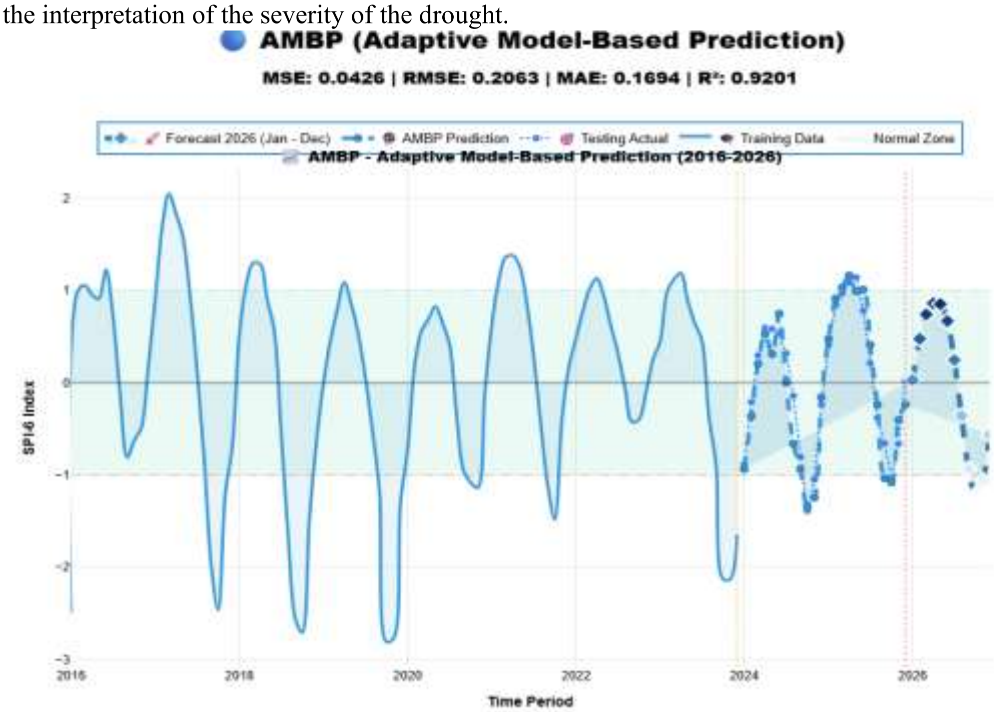
a) Time series forecasting visualization using SSA

*name of corresponding author

b) Visualization of SPI-6 2026 prediction distribution

Fig. 2 Visualization of SPI-6 Drought Index Forecast Results and Distribution for 2026 Using the SSA Method

Fig. 2 shows the results of forecasting the SPI-6 drought index time series using the SSA method, as shown in subfigure (a). The visualization shows that the model is able to represent the general temporal pattern of SPI-6, including seasonal fluctuations and long-term trends. The R^2 value of 0.918 indicates that approximately 91.8% of the variation in historical SPI-6 data can be explained by the SSA model. However, the MSE value of 0.436 and the RMSE value of 0.208 show that the prediction error rate is still relatively high, especially in periods with extreme fluctuations. In addition, the MAE value of 0.163 reflects a significant average absolute deviation between the prediction results and the actual data. Subfigure (b) The figure shows the distribution of SPI-6 predictions throughout 2026, which reveals variations in hydroclimatic conditions from month to month. The visualization results show that SPI-6 values are relatively positive in the period from January to May, indicating normal to wet conditions, then decline towards dry conditions in the period from August to October. Although the seasonal transition pattern was successfully captured by the SSA model, the magnitude of the error values generated indicates that the intensity of the predicted drought is still lacking in precision. In some months, the amplitude of the prediction tends to be reduced or even exaggerates the actual conditions, thus potentially causing bias in the interpretation of the severity of the drought.



c) Visualization of time series forecasting using AMBP

*name of corresponding author

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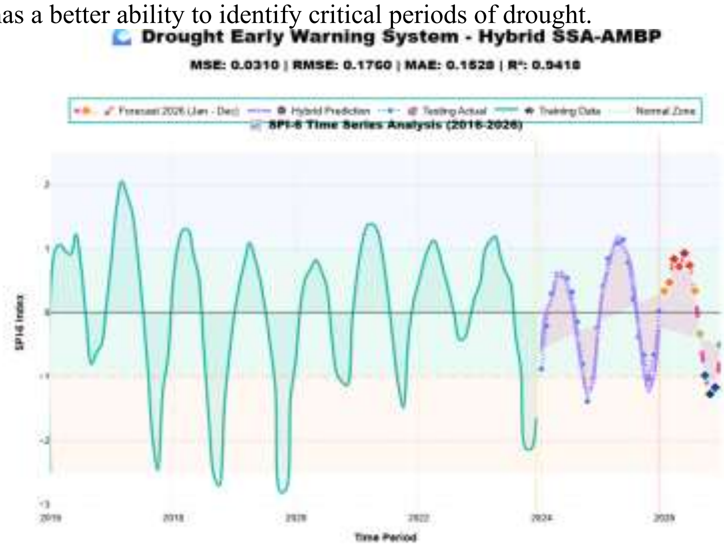
d) Visualization of SPI-6 2026 prediction distribution

Fig. 3 Visualization of SPI-6 Drought Index Forecast Results and Distribution for 2026 Using the AMBP Method

Fig. 3 shows the results of forecasting the SPI-6 drought index time series using the AMBP method, as shown in subfigure (c). The visualization shows that the AMBP model is able to represent the temporal pattern of SPI-6 with a higher level of accuracy compared to the SSA method. This is indicated by an MSE value of 0.0426 and an RMSE value of 0.2063, which indicate a significant reduction in the prediction error rate. This decrease in the MSE value shows that AMBP is capable of producing estimates that are closer to the actual data. In addition, the MAE value of 0.1694 reflects an average absolute deviation that is relatively comparable to the SSA method, while the R^2 value of 0.9201 indicates that approximately 92.0% of the SPI-6 data variation can be explained by the AMBP model. Subfigure (d) This visualization shows the distribution of SPI-6 prediction results throughout 2026 using the AMBP method. It shows that the AMBP model is more responsive to short-term changes than SSA. SPI-6 values from January to June were in the normal to wet range, then declined and entered a dry phase from August to November, with the highest intensity occurring in October and November. This pattern indicates that the AMBP method has a better ability to identify critical periods of drought.



e) Time series forecasting visualization using Hybrida SSA-AMBP

f) Visualization of SPI-6 2026 prediction distribution

Fig. 4 Visualization of SPI-6 Drought Index Forecast Results and Distribution for 2026 Using the SSA-AMBP Method

*name of corresponding author

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.Fig. 4 shows the results of SPI-6 drought index time series forecasting using the hybrid SSA–AMBP method, as presented in subfigure (e). The visualization indicates that the integration of SSA for signal denoising and dominant component extraction with AMBP as an adaptive predictive model improves the quality of SPI-6 temporal pattern modeling. This is reflected in the MSE value of 0.0310, RMSE of 0.1760, and MAE of 0.1528. In addition, the R^2 value of 0.9418 indicates that approximately 94.18% of the variation in historical SPI-6 data can be explained by the hybrid model. These values demonstrate that the SSA–AMBP method is capable of producing more accurate and stable predictions than the separate use of SSA and AMBP, particularly in representing extreme fluctuations and seasonal dynamics. Subfigure (f) presents the distribution of SPI-6 predictions throughout 2026 using the SSA–AMBP method. The results show that SPI-6 values from January to July fall within the normal to wet category, with peak values occurring between March and May. From August to November, SPI-6 values decline significantly and enter the dry category, with the most severe conditions observed in October and November. This distribution pattern indicates a clear seasonal transition from relatively wet conditions to dry conditions in the second half of 2026. Compared to the SSA and AMBP methods, the hybrid SSA–AMBP produces a smoother and more consistent prediction pattern and demonstrates a stronger ability to suppress random fluctuations.

Table 3 2026 Forecast Results (January - December) Based on SPI-6

Month	SPI-6	Approximate Rainfall (mm)	classification
January	0.335	5.0	Normal
February	0.472	5.5	Normal
March	0.835	6.9	Normal
April	0.719	7.2	Normal
May	0.927	6.5	Normal
June	0.738	5.0	Normal
July	0.337	2.5	Normal
August	-0.331	0.1	Normal
September	-0.982	0.0	Normal
October	-1.274	0.0	Moderately Dry
November	-1.170	1.9	Moderately Dry
December	-0.507	4.3	Normal

Table 3 shows that the 2026 Drought Category, which refers to SPI-6, indicates that drought conditions are generally normal throughout most of 2026. SPI-6 values from January to July 2026 are in the positive range, approaching zero, indicating relatively stable water availability that supports agricultural activities. During this period, rainfall is still adequate to maintain soil moisture and meet crop water requirements, so the risk of water stress is low. However, from August to September 2026, the SPI-6 value declines to negative figures, although still within the normal category, signaling the beginning of a transition to drier conditions. The significant decrease in rainfall during this period indicates a reduction in natural water supply, which has the potential to reduce groundwater reserves, especially on rain-fed agricultural land.

More severe drought conditions were observed from October to November 2026, when the SPI-6 value fell into the moderate dry category. During this period, rainfall was almost zero, resulting in a significant water deficit. These moderately dry conditions increased the risk of water stress on crops, reduced vegetative growth, and potentially decreased crop yields if not accompanied by adequate irrigation or water management strategies. In addition, drought in this phase can reduce the availability of surface water and groundwater, which has the potential to cause conflicts over water use at the local level. Entering December 2026, the SPI-6 value returned to the normal category, indicating a recovery in hydrometeorological conditions. The identified seasonal drought patterns emphasize the importance of early warning systems, so that mitigation measures such as crop pattern adjustments, irrigation management, and water conservation can be implemented appropriately to minimize the impact of drought on the agricultural sector and water resources.

DISCUSSIONS

Based on the results of the study, the hybrid SSA–AMBP method demonstrated the most optimal performance in predicting the SPI drought index compared to the standalone SSA and AMBP methods. This was indicated by the lowest RMSE value of 0.176 and the highest coefficient of determination (R^2) of 0.941, reflecting a relatively small prediction error and an excellent capability of the model in representing actual data variations. Meanwhile, the SSA and AMBP methods also showed fairly good performance, with RMSE values of 0.208 and 0.206, and R^2 values of 0.918 and 0.920, respectively. Although the hybrid SSA–AMBP model achieved a high coefficient

*name of corresponding author

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of determination ($R^2 > 0.94$), the risk of overfitting was mitigated through temporal data splitting and consistent performance between training and testing phases. The relatively small gap between training and testing RMSE values indicates that the model maintains good generalization capability and does not excessively memorize training data patterns. These results indicate that both individual methods are capable of capturing the main patterns of SPI data effectively; however, they still exhibit limitations in minimizing prediction errors.

The superior performance of the hybrid SSA–AMBP model in this study demonstrates that the integration of SSA's capability in noise reduction and dominant pattern extraction with AMBP's adaptive characteristics in modeling nonlinear relationships can produce predictions that are more accurate, stable, and consistent. Despite the promising performance, several limitations should be acknowledged. The model evaluation was conducted using a single regional dataset and monthly temporal resolution, which may limit its generalization to other climatic regions or higher-frequency data. In addition, the study did not incorporate operational validation, real-time data integration, or uncertainty analysis, which are essential components in practical early warning systems. Therefore, the proposed model should be interpreted as a predictive analytical framework rather than a fully implemented decision-support system.

The performance of the model in this study shows a relatively high level of predictive accuracy. Previous studies reported different RMSE values, such as 0.758 in temperature prediction (Ruslana & Zuliarso, 2025), 5.181001 in rainfall trend prediction (Shaharudin et al., 2024), and 191.0566 in climate-related modeling (Aswi & Ahmar, 2025). However, these RMSE values cannot be directly compared because they are derived from different datasets, measurement scales, temporal resolutions, and modeling contexts. Therefore, the superiority of the proposed model should be interpreted within the scope of the SPI-6 dataset used in this study rather than through absolute RMSE magnitude comparisons.

CONCLUSION

Based on the analysis results, it can be concluded that the hybrid SSA–AMBP method demonstrates the best performance in predicting the SPI-6 drought index compared to the standalone SSA and AMBP approaches. During the model training phase, the hybrid SSA–AMBP achieved an RMSE value of 0.149 with an R^2 of 0.983, indicating a very low prediction error and a strong capability in representing the variability of the observed data. In the model evaluation phase, this approach consistently maintained superior performance, with an RMSE value of 0.176 and an R^2 of 0.941. These results confirm that the hybrid SSA–AMBP model provides high predictive accuracy and strong stability in capturing the temporal dynamics of the SPI-6 drought index. The integration of SSA for signal denoising and dominant component extraction with AMBP as an adaptive forecasting mechanism has been proven to enhance overall prediction quality. Furthermore, the SPI-6 projections for 2026 exhibit a clear seasonal pattern, with predominantly normal conditions and a moderate dry period occurring between October and November. These findings indicate that the hybrid SSA–AMBP approach has substantial potential to serve as a predictive foundation for the development of an agrometeorological parameter-based drought early warning framework.

Further research should expand the scope of data, both in terms of time range and temporal resolution, such as the use of daily or decadal data, so that drought dynamics can be analyzed in greater detail and comprehensively. In addition, the integration of other supporting variables, such as vegetation indices, evapotranspiration, soil moisture, and hydrological data, is expected to improve the sensitivity and accuracy of the model in detecting changes in environmental conditions. Future research also needs to consider the application of more complex artificial intelligence methods, such as deep learning, hybrid ensemble, or deep learning-based approaches, to improve the ability to predict more complex nonlinear patterns. In addition, model validation in regions with different climatic characteristics needs to be carried out to test the level of generalization and reliability.

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