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Research Article

OPTIMIZING FLOOD EARLY WARNING SYSTEMS: THE ROBUSTNESS OF THE ADDITIVE HOLT-WINTERS MODEL IN FORECASTING SEASONAL RIVER STAGES

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Abstract
Rising flood risks in tropical riparian zones due to climate variability necessitate robust early warning systems. This study evaluates the effectiveness of the Additive Holt-Winters Exponential Smoothing model in forecasting seasonal river water levels to enhance flood mitigation strategies for the Bengawan Solo River. A quantitative approach was employed using secondary data from the Jurug Observation Post (January 2021–January 2025), aggregated into 49 monthly observations. The analysis proceeded through four systematic stages: stationarity testing (ADF), seasonal decomposition, parameter optimization (α, β, γ) using RStudio, and forecast verification. Decomposition analysis revealed a distinct additive seasonal pattern with consistent peaks in February and a historical downward trend ($b_t < 0$), validating the model selection. The model achieved exceptional accuracy with a Mean Absolute Percentage Error (MAPE) of 0.4725%, outperforming traditional intuitive monitoring. Forecasts for 2025 indicate water levels will remain below the alert threshold, though seasonal peaks require vigilance. Unlike complex neural network models requiring extensive datasets, this study offers novelty by demonstrating that the parsimonious Holt-Winters method provides a strategic balance between computational efficiency and high accuracy ($< 1\%$ error) in data-limited regions. These findings imply that disaster management agencies can shift from reactive emergency response to proactive maintenance of flood control infrastructure based on reliable medium-term projections.

Keywords: Bengawan Solo, Forecasting, Holt-Winters, River Water Level.

INTRODUCTION

Water plays a fundamental role in sustaining human life and supporting socio-economic systems, including drinking water supply, irrigation, fisheries, hydropower generation, transportation, and industry. However, water also constitutes one of the most significant sources of natural hazards, particularly flooding. In recent decades, climate change and increasing precipitation intensity have altered hydrological regimes, resulting in greater variability of river discharge and heightened flood risk in many tropical regions.

Flooding remains one of the most frequent and destructive disasters in Indonesia. According to national disaster statistics reported by BNPB, 9,147 flood events occurred between 2014 and 2024, indicating a persistent and systemic vulnerability. Floods generally occur when river discharge exceeds the capacity of natural channels or engineered drainage systems. Increasing rainfall variability has intensified uncertainty in river stage behavior, making conventional reactive disaster response strategies insufficient. These conditions underscore the urgency of developing reliable river stage forecasting models capable of supporting anticipatory flood mitigation. Since river water levels are recorded periodically at monitoring stations, the resulting data form a structured time series suitable for statistical forecasting approaches (Vulandari et al., 2019).

The Bengawan Solo River Basin represents one of the most flood-prone regions in Indonesia. Recurrent overflow events, including the January 13, 2025 flood affecting residential areas in Lamongan Regency, illustrate that existing flood management strategies have not yet achieved optimal preventive performance. The seasonal and trend-dominated hydrological behavior of the Bengawan Solo River suggests that systematic time series modeling may offer strategic value for medium-term forecasting. Mathematical and numerical modeling approaches are therefore essential to interpret recurring patterns embedded in historical river stage data (Atmanegara, 2022; Hajrulla et al., 2025).

Time series forecasting methods have been widely applied in hydrology due to their capacity to capture trend and seasonal components. Among them, the Holt-Winters Exponential Smoothing technique is recognized for its ability to decompose time series into level, trend, and seasonal components while assigning greater weight to recent observations (Amalia et al., 2024). Prior research has demonstrated the effectiveness of Holt-Winters in forecasting river discharge (V. Kumar et al., 2024), meteorological drought (Raha & Gayen, 2021), rainfall variability (Puah et al., 2016; Sinay et al., 2017), and streamflow dynamics (Pichura et al., 2020; Tanti et al., 2020; Kurniawan et al., 2022; Rentería-Mena & Giraldo, 2024). The method has also shown strong predictive performance in non-hydrological domains such as economic forecasting and environmental concentration modeling (Ersita et al., 2024; Tanti et al., 2021; Hani'ah & Kurniawan, 2023).

However, despite extensive applications, several critical gaps remain in the current body of knowledge. First, the hydrological forecasting literature increasingly prioritizes complex architectures, such as ARIMA variants and machine learning algorithms (Tanti et al., 2021; Banat I et al., 2024; Dhital, 2024; Liu et al., 2024; Majeed et al., 2024). While powerful, these models often prioritize predictive precision at the expense of interpretability and operational feasibility. They typically necessitate extensive datasets and advanced parameter tuning, rendering them impractical for resource-constrained river basins in developing regions. Second, while Holt-Winters has been widely applied to rainfall and discharge forecasting, its systematic evaluation specifically as a medium-term river stage early warning tool in tropical riparian zones remains limited. Third, there is a scarcity of studies that explicitly assess whether a parsimonious seasonal model can achieve operationally reliable accuracy for disaster preparedness, particularly in basins characterized by stable additive seasonality like the Bengawan Solo.This research gap indicates the need for an empirical assessment of whether a computationally efficient, interpretable seasonal model can provide sufficient predictive accuracy to support proactive flood mitigation. Addressing this gap is particularly urgent given increasing hydrological variability and the demand for scalable forecasting frameworks suitable for data-limited environments.

To respond to this problem, this study proposes a structured problem-solving framework: (1) modeling historical river stage data using the Additive Holt-Winters Exponential Smoothing method; (2) evaluating forecasting performance using standard accuracy metrics, namely MAPE; and (3) interpreting the model outputs within a flood early warning context to assess their operational relevance for medium-term preparedness planning.

Therefore, this study aims to implement the Additive Holt-Winters Exponential Smoothing method to forecast river stage levels in the Bengawan Solo River, to rigorously evaluate its predictive accuracy and stability in capturing seasonal and trend dynamics, and to assess the feasibility of employing this parsimonious time series approach as a practical component of a flood early warning system in tropical river basins. By aligning the seasonal time series framework with the hydrological characteristics of the Bengawan Solo River, this research seeks to provide an interpretable, data-efficient, and operationally applicable forecasting model that supports proactive flood risk mitigation and strengthens anticipatory disaster management strategies in Indonesia.

RESEARCH METHOD

This study adopts a quantitative descriptive approach grounded in a case study methodology. The analytical process follows a structured data-driven workflow consisting of data collection, preprocessing, modeling, and evaluation stages, which is consistent with established quantitative research frameworks (Sanjaya et al., 2022). The primary focus lies in the application of the additive Holt-Winters Exponential Smoothing method to forecast the river stage of the Bengawan Solo River at the Jurug Hydrological Observation Station. This methodological framework was selected due to the Holt-Winters method's robust capability to capture both seasonal patterns and underlying trends within hydrological time series data (L. Kumar et al., 2024; Alexander D. Pulido-Rojano et al., 2025). The method further allows for parameter flexibility, enabling the development of forecasting models that are responsive to temporal variations in the data pattern. In the context of this research, the additive form of the Holt-Winters model was employed. This selection aligns with the characteristics of the Bengawan Solo River water level data, which exhibit stable seasonal fluctuations over the years, without any significant amplitude changes across the seasonal cycles (Carvalho et al., 2020; Pleños, 2022; Tanti et al., 2025).

The data for this study were collected from the administrative area of the Jurug Observation Station, located in Surakarta, Central Java. This station serves as one of the strategic monitoring points within the Bengawan Solo River surveillance system, as the data obtained from this site have historically been used to support flood control policy-making and water resource management decisions by Balai Besar Wilayah Sungai Bengawan Solo. The dataset utilized in this study is secondary data published by the Ministry of PUPR, Directorate General of Water Resources. The unit of analysis in this study consists of daily water level records of the Bengawan Solo River, measured consistently at 18:00 WIB from January 2021 to January 2025.

This study was conducted through a series of stages, namely:

Collecting Water Level Data of the Bengawan Solo River at Jurug Station from January 2021–January 2025. The initial stage involved the systematic acquisition of river stage data from the Bengawan Solo River at the Jurug Hydrological Observation Station, spanning the period from January 2021 to January 2025. These data represent daily observations recorded consistently at 18:00 Western Indonesian Time (WIB), which were subsequently aggregated into monthly averages, resulting in a total of 49 monthly observation points. In time series analysis, statistical power is not determined solely by the number of observations (N), but by the length of the seasonal cycles captured. According to (Hyndman & Athanasopoulos, 2018), robust seasonal decomposition requires a minimum of two full cycles. This study utilizes four full cycles (4 × 12 months), ensuring sufficient statistical power to distinguish between trend, seasonal, and random components without overfitting.

To ensure systematic data acquisition, the operational definitions and specifications of the variables used in this study are detailed in Table 1.

Table 1. Summarizes The Data Collection Instrument And Operational Definitions Used In This Study

Variable	Operational Definition	Unit	Scale	Frequency	Source
River Water Level	The average height of the water surface measured from the zero gauge point at the Jurug Observation Post.	Meters (m)	Ratio	Monthly (aggregated from daily maximum values)	Bengawan Solo River Basin Center (BBWS)
Time Period	The chronological sequence of observations used for model training and testing.	Month/Year	Interval	Monthly (January 2021 – January 2025)	–

As outlined in Table 1, the river water level is measured in meters above sea level (masl) on a monthly temporal scale, serving as the primary input for the modeling process. Exploring Data through Descriptive Statistical Analysis and Time Series Visualization. Upon completion of the data collection process, an exploratory analysis was conducted using descriptive statistics and time-series visualization techniques. As emphasized by (Kurniawan et al., 2023.), such descriptive and visual analyses serve to provide an overarching perspective on the data distribution. Within the context of this study, this step elucidates the temporal behavior of river stage measurements at the Jurug station throughout the observation window.

Performing Assumption Tests on the Data. Subsequent analytical steps involved evaluating three key statistical assumptions. First, the stationarity of the series was examined using the Augmented Dickey-Fuller test. As noted by Johanis Gontung and Akbar Manaf, the ADF test is a unit root testing method employed to ascertain the stationarity of time series data (Hidayah et al., 2021). Its application is crucial in hydrological studies for checking the stationarity of data like rainfall and streamflow (Al-Najjar et al., 2020; Jan et al., 2023; Nair et al., 2024). The null hypothesis (H_0) posits the presence of a unit root, implying non-stationarity. The test statistic is computed using the following model:

$$\Delta Y_1 = \beta_1 + \beta_2 t + \delta Y_{t-1} + \alpha_i \sum_{i=1}^{m} \Delta Y_{t-1} + \epsilon_t \ldots (1)$$

The ADF test can be performed using statistical software such as Minitab or RStudio. A p-value less than 0.05 leads to the rejection of the null hypothesis, indicating that the time series is stationary. Second, the seasonal component was assessed via seasonal plots to observe recurring patterns across specific periods. Third, trend analysis was carried out using a trend plot, in which the slope of the fitted regression line was examined. An upward slope indicates a positive trend, whereas a downward slope suggests a declining trend over time.

Initialization of Smoothing Level (St), Trend (bt), and Seasonality (It) Components). According to (Dobler & Anderson-Cook, 2005), initial values for the smoothing components can be estimated via linear regression, wherein the intercept corresponds to the level component, and the slope signifies the trend (L. Kumar et al., 2024; Lima et al., 2019). A simple linear regression model was fitted using one or two complete seasonal cycles of historical data, with actual values as the dependent variable and time indices as the independent variable. The resulting intercept and slope serve as estimators for the initial level and trend components, respectively (Trull et al., 2020). The seasonal indices were subsequently computed from the residuals of the trend regression. These residuals, representing the discrepancy between observed values and the predicted trend, were regressed on seasonal dummy variables without an intercept term. The resulting coefficients provide estimates of the initial seasonal indices. The seasonal indices were subsequently computed from the residuals of the trend regression. These residuals, representing the discrepancy between observed values and the predicted trend, were regressed on seasonal dummy variables without an intercept term. The resulting coefficients provide estimates of the initial seasonal indices.

Optimization of Smoothing Parameters (α, β, γ)). Following confirmation of the underlying assumptions, the Holt-Winters exponential smoothing parameters were estimated. These include: α for the level, β for the trend, and γ for the seasonal component. These parameters determine the respective weights assigned to the level, trend, and seasonality in the forecasting model and are critical to achieving optimal forecasting accuracy (Rumbe et al., 2024). Parameter estimation was conducted iteratively or by employing statistical optimization algorithms available in RStudio (Buczak et al., 2018; Heydari et al., 2019; Alexander D Pulido-Rojano et al., 2025; Tüz & EBESEK, 2023). The selection of appropriate optimization algorithms is vital to enhance model performance and minimize errors (Arkabaev et al., 2025). The selected parameters must reside within the interval and are chosen to minimize forecast error, typically assessed via measures such as Mean Squared Error or Mean Absolute Percentage Error.

Computation of Smoothed Values and Forecasting Implementation. Upon determination of the optimal smoothing parameters (α, β, γ), smoothed values for the level (St), trend (bt), and seasonal (It) components were recursively calculated at each time point. As described by Mulyana (Parwati, 2020), the Holt-Winters Exponential Smoothing method combines Holt's linear trend model with Winters' seasonal adjustment. There are two principal variants of this model: additive and multiplicative. The additive model assumes that seasonal fluctuations are constant in magnitude over time and independent of the series level, while the multiplicative model assumes that seasonal fluctuations vary proportionally with the level of the series (Pleños, 2022). Given the nature of the seasonal pattern in the dataset, the additive version of the Holt-Winters method was deemed appropriate for this study. The following formulae describe the additive model structure used in the forecasting process:

Level Smoothing Equation:

$$S_t = \alpha(y_t - I_{t-l}) + (1-\alpha)(S_{t-1} + b_{t-1}) \ldots (2)$$

Trend Smoothing Equation:

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \ldots (3)$$

Seasonal Smoothing Equation:

$$I_t = \gamma(y_t - S_t) + (1-\gamma)I_{t-l} \ldots (4)$$

The final step in the modeling process is generating forecasts for future periods n, using the following formula of the additive Holt-Winters method:

$$Ft{+}n = St + nbt + It{-}l{+}[((n{-}1) mod\ l){+}1] \ldots (5)$$

Explanation:
α = smoothing parameter for level ($0 < \alpha < 1$),
β = smoothing parameter for trend ($0 < \beta < 1$),
γ = smoothing parameter for seasonality ($0 < \gamma < 1$),
n = number of periods ahead to forecast,
l = length of the seasonal cycle (e.g l=3, l=4, l=6, or l =12),
y_t = actual value at time t,
F_t = forecasted value at time t,
S_t = smoothed level component at time t,
b_t = smoothed trend component at time t,
I_t = smoothed seasonal component at time t,
S_{t-1} = level component at time t–1,
b_{t-1} = trend component at time t-1.

In the forecasting process, it is crucial to establish initial values for the model components. In this study, the initial level and trend were determined using simple linear regression, following the formulation yt = a + bt + εt (Dobler & Anderson-Cook, 2005).

Forecast Accuracy Evaluation Using MAPE. To assess the forecasting performance, the study employs the Mean Absolute Percentage Error (MAPE), a widely used metric in time series forecasting. As stated by (Amalia et al., 2024), the lower the MAPE value, the higher the accuracy of the forecast

MAPE Formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\left(\frac{A_t - F_t}{A_t}\right) \times 100\%\right| \ldots (6)$$

where:
n: total number of observations,
A_t: actual value at time t,
F_t : forecasted value at time t.

According to (Lewis, 1982) the interpretation of MAPE values can be classified into four distinct categories, as further referenced by (Ngabidin et al., 2023). These categories are presented in Table 2.

Table 2. MAPE Value Interpretation Criteria

MAPE Value	Forecasting Results Category
MAPE ≤ 10%	Very Accurate
10% < MAPE ≤ 20%	Good
20% < MAPE≤ 50%	Reasonable
MAPE > 50%	Not Accurate

The classification in Table 2 establishes that a MAPE below 10% indicates a 'very accurate' forecasting model, which is the target precision for this study. Interpretation Based on Flood Alert Status. In the context of flood risk management, particularly in the Bengawan Solo River Basin, the river stage level serves as a critical indicator for determining disaster alert levels (Shrestha et al., 2025). According to the BBWS Bengawan Solo, three flood alert categories are defined based on river stage height (in meters above sea level). These categories serve as a reference for emergency decision-making, such as opening sluice gates or issuing evacuation orders (Ningtias et al., 2025; Susandi et al., 2018). The specific flood alert thresholds applicable to the Jurug Observation Station are summarized in Table 3.

Table 3. Flood alert status category observation post jurug

Category	River Stage Height (masl)
Green Alert	≥ 82,98 masl
Yellow Alert	≥ 83,98 masl
Red Alert	≥ 84,98 masl

Referring to Table 3, the critical ‘Red Alert’ status is triggered when water levels exceed 84.98 masl, necessitating immediate emergency response. Statistical analysis was conducted through four systematic stages using RStudio and Minitab 22. First, data exploration was performed to identify missing values and visualize initial patterns. Second, the stationarity of the time series was evaluated using the Augmented Dickey-Fuller test, followed by seasonal decomposition to isolate the trend, seasonal, and error components. Third, the Additive Holt-Winters Exponential Smoothing model was applied, as the seasonal variations were constant relative to the trend (Hendri & Fadhlia, 2024; Lukman & Tanan, 2021). The smoothing parameters were optimized by minimizing the Sum of Squared Errors. Finally, forecast accuracy was assessed using Mean Absolute Percentage Error to determine the model's reliability for early warning implementation (Hakim et al., 2023).

The analytical power of this study is derived from the temporal structure of the dataset rather than the number of observations alone. The dataset consists of 49 monthly observations, representing more than four complete seasonal cycles. In time series forecasting, capturing multiple seasonal cycles is essential for reliably estimating trend and seasonal components. Previous studies suggest that a minimum of two full seasonal cycles is required for robust seasonal modeling. Therefore, the availability of more than four seasonal cycles in this study provides sufficient analytical power to identify stable seasonal patterns, optimize model parameters, and generate reliable medium-term forecasts without overfitting. The systematic workflow of this study, ranging from data preprocessing to forecast verification, is visualized in Figure 1.

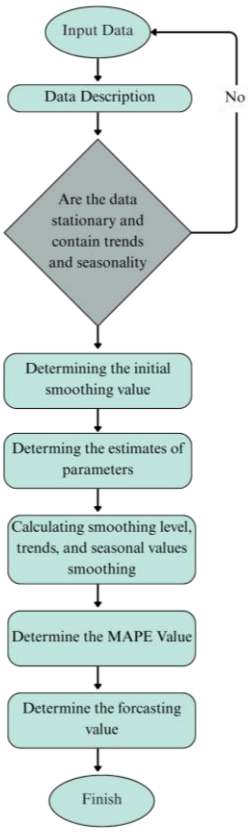

Figure 1. Research flowchart

As depicted in Figure 1, the research stages proceed sequentially from stationarity testing to parameter optimization, ensuring a structured analytical framework.

RESULTS AND DISCUSSION

Forecasting serves as a strategic approach for planning and anticipating potential disasters such as flooding. Therefore, selecting an appropriate forecasting method is crucial to ensure that the predicted outcomes closely align with actual events. Historical data play a fundamental role in constructing reliable forecasting models. In this study, the data utilized consist of river stage measurements from the Bengawan Solo River at the Jurug Observation Station. The dataset comprises daily observations collected at 18:00 Western Indonesian Time (WIB) from January 2021 to January 2025. These daily measurements were subsequently averaged on a monthly basis to generate 49 monthly observation points. The data utilized in this study were accessed in February 2025. Therefore, the river stage data for the period from February to December 2025 had not yet been published at the time of access. As such, the forecasting process was carried out to estimate river stage values for these months. A descriptive summary of the historical river stage data collected from 2021 to 2025 is presented in Table 4.

Table 4. Description of the water level data of the Bengawan Solo River

Mean	Standard Deviation	Minimum	Maximum
78.9637	0.899638	77.77	81.49

Based on Table 4, it can be observed that the average water level of the Bengawan Solo River at the Jurug Observation Station from January 2021 to January 2025 was 78.9637 meters above sea level (masl) with a standard deviation of 0.899638, indicating relatively moderate fluctuations over the observation period. The maximum water level of 81.49 masl occurred in February 2023, whereas the lowest level of 77.77 masl was recorded in August 2024. To visually identify the temporal behavior and potential patterns within the dataset, a time series plot is displayed in Figure 2.

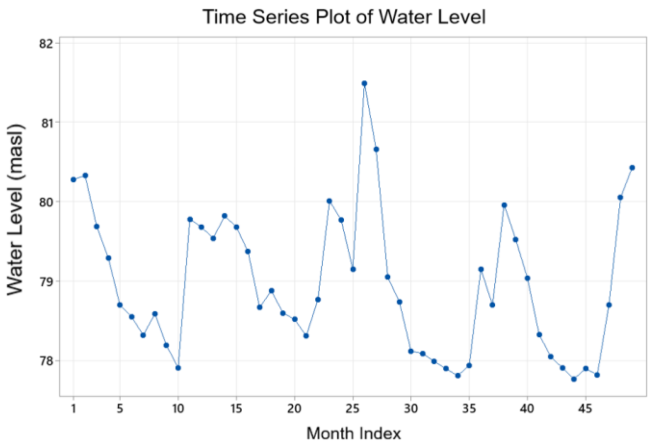

Figure 2. Time series plot of Bengawan Solo river water level

Visual inspection of Figure 2 reveals that each time index from Month 1 to Month 49 represents sequential monthly observations, Month 1 corresponds to January 2021, Month 2 to February 2021, etc. up to Month 49, representing January 2025. To determine the suitability of the data for forecasting using the Holt-Winters Exponential Smoothing method, assumption tests were conducted, including stationarity test, seasonality test, and trend analysis. The first assumption test was to assess the stationarity of the data. Using Minitab 22, the Augmented Dickey-Fuller (ADF) test was performed. The results of the stationarity test are summarized in Table 5 below:

Table 5. *Augmented Dikey Fuller test*

Test Statistic	P-Value
-4,23481	0,001

As indicated in Table 5, the resulting p-value of 0.001 is less than the significance level of 0.05, confirming that the time series is stationary. To verify the presence of recurring cyclical patterns, a seasonal visualization of the water levels is presented in Figure 3.

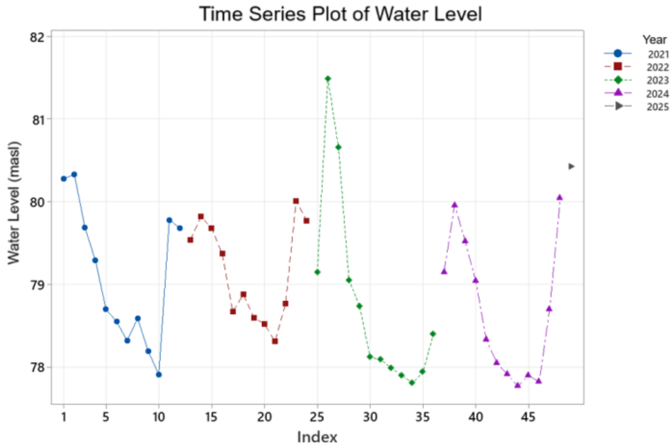

Figure 3. Seasonal time series plot of Bengawan Solo river water level

Figure 3 explicitly demonstrates a consistent seasonal pattern, where the recurring rise and fall in river stage levels. The recurring rise and fall in river stage levels each year reflect significant seasonality, where low-water seasons typically occur mid-year and high-water levels emerge toward the end of the year. The consistent shape of the seasonal pattern across years indicates that the additive seasonal model is appropriate (Supatmi et al., 2019). The time series visualization of river stage levels from 2021 to 2025 clearly reveals a consistent seasonal pattern. The observed cyclical fluctuations, characterized by recurring rises and falls in water levels, indicate a significant seasonal influence embedded in the data. Typically, low-water seasons occur during the mid-year months, while water levels begin to rise again toward the end of each year. The annual consistency in the pattern's structure suggests that the seasonal component follows an additive form. To examine the presence of a long-term trend, a trend plot was generated using a linear regression line fitted to the time series. The long-term trajectory of the river stage is illustrated in the trend analysis plot shown in Figure 4.

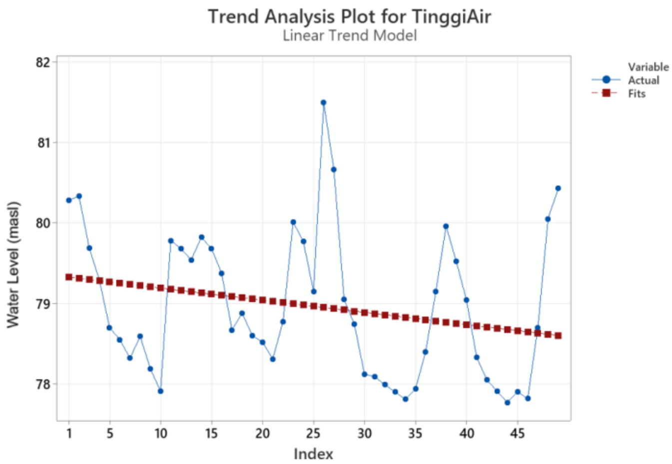

Figure 4. Bengawan Solo river water level trend plot

As shown in Figure 4, the trend line exhibits a consistently negative slope, indicating a downward trend in the average river stage levels over time. This trend implies a gradual decline in river height across the observed period. Based on these findings, it can be concluded that the dataset is stationary and has a trend pattern and seasonal pattern. These characteristics make the dataset highly suitable for modeling using the Additive Holt-Winters Exponential Smoothing Method. Specifically, the seasonal visualization (Figure 3) reveals a distinct additive pattern with consistent peaks in February and troughs in August, strictly following the monsoonal precipitation cycle in Java. Meanwhile, the trend analysis (Figure 4) exhibits a gradual downward trajectory (b_t< 0). This declining trend might indicate a shift in hydrological discharge intensity or changes in the catchment area's retention capacity over the observed period. This combination of a stable seasonal signal and a dynamic linear trend confirms that the Additive Holt-Winters method is the most appropriate mathematical framework for this dataset.

The initial level value was determined based on the intercept, while the initial trend value was derived from the slope of the simple linear regression model. Based on the results of the regression analysis, the following equation was obtained: $Y = 79{,}793 - 0{,}105140b$.

From this regression equation, it can be concluded that the initial smoothing level is 79,793, and The initial smoothing trend -0,105140. The initial seasonal values were estimated from the residuals of the regression model. These residuals were subsequently regressed on seasonal dummy variables (without an intercept), resulting in the set of initial seasonal indices presented in Table 6.

Table 6. Seasonal Initial Value

Month	Initial Value
1	0,66292
2	0,03832
3	0,21665
4	-0,16001
5	-0,50168
6	-1,13334
7	-1,09001
8	-1,33167
9	-1,22334
10	-1,51500
11	-1,41167
12	0,15667

The indices in Table 6 quantify the specific seasonal effect for each month, with negative values indicating months below the trend line. The process of determining the optimal values for the smoothing parameters α, β, and γ was carried out using the RStudio software. This platform facilitates iterative optimization to identify parameter values that minimize forecasting errors in exponential smoothing models. For this study, the optimal parameters for the additive Holt-Winters Exponential Smoothing model were found to be α= 0,4576626, β=0, and γ=0,85159. Following the estimation of these parameters, the next step involved computing the smoothed values for the level (St), trend (bt), and seasonal (It) components at each time point. These calculations were performed iteratively, with each value derived based on the results from the preceding period. This recursive approach ensures that the smoothing process accounts for the evolving structure of the time series over time. The resulting smoothed values for each component, covering the period from Month 13 to Month 49, are presented in Table 7 below.

Table 7. Smoothing result values in the 13th to 49th months

Month	Smoothing level value	Trend smoothing value	Seasonal smoothing value
13	78.90710677	-0.10513986	0.639188303
14	78.75971892	-0.10513986	1.06771096
15	78.79875072	-0.10513986	0.855894749
16	78.87696023	-0.10513986	0.460795313
17	78.86035283	-0.10513986	-0.205922456
18	79.02348667	-0.10513986	-0.190666206
19	79.07294513	-0.10513986	-0.500133324
20	78.9994766	-0.10513986	-0.485046425
21	79.00209459	-0.10513986	-0.711045257
22	79.25481447	-0.10513986	-0.547748925
23	79.27030437	-0.10513986	0.718481259
24	79.15584074	-0.10513986	0.615798971
25	78.80361379	-0.10513986	0.389839795

Month	Smoothing level value	Trend smoothing value	Seasonal smoothing value
26	79.48739964	-0.10513986	1.863857166
27	79.57532267	-0.10513986	1.05072462
28	79.06699207	-0.10513986	0.053914442
29	78.95456176	-0.10513986	-0.213279634
30	78.60285357	-0.10513986	-0.43949121
31	78.54001071	-0.10513986	-0.457449206
32	78.45325771	-0.10513986	-0.466491284
33	78.46844989	-0.10513986	-0.589611897
34	78.36076492	-0.10513986	-0.550317328
35	77.78235327	-0.10513986	0.240877937
36	77.72617764	-0.10513986	0.665211338
37	78.14237151	-0.10513986	0.915944939
38	78.0641931	-0.10513986	1.891065371
39	78.19256283	-0.10513986	1.286371368
40	78.49870723	-0.10513986	0.468962905
41	78.46208507	-0.10513986	-0.144134832
42	78.41760656	-0.10513986	-0.378274672
43	78.33763014	-0.10513986	-0.432055464
44	78.23432139	-0.10513986	-0.464643413
45	78.29413703	-0.10513986	-0.423146671
46	78.27198062	-0.10513986	-0.46657438
47	78.30060698	-0.10513986	0.375868428
48	78.73977511	-0.10513986	1.214501008
49	79.03711281	-0.10513986	1.3221061

The smoothed values in Table 7 demonstrate how the level, trend, and seasonal components evolve iteratively over the observation period. The performance evaluation of the Holt-Winters Exponential Smoothing model was conducted by measuring the accuracy of the forecasted results. The model's predictive accuracy was assessed using the Mean Absolute Percentage Error metric (Iqbal et al., 2023; Van et al., 2020). These values were obtained by comparing the forecasted outcomes against actual observations, which had been reserved as test data. In general, the smaller the MAPE value, the better the model's ability to capture the underlying structure of the data (Van et al., 2020).

For this study, the accuracy assessment was carried out using Minitab 22, which produced a MAPE value of 0.476124%. This result implies that the average relative forecasting error is less than half a percent, indicating that the model possesses an exceptionally high level of predictive accuracy. According to (Lewis, 1982), a MAPE value below 10% is already considered very good. Therefore, a MAPE of less than 1% not only confirms the robustness of the model but also demonstrates its high reliability and precision in capturing the historical pattern of river stage fluctuations. This exceptional accuracy is largely attributed to the data aggregation process, which helps in filtering high-frequency noise and highlighting seasonal signals. By converting daily fluctuations into monthly averages, high-frequency noise (random volatility) is filtered out, leaving a clear macro-seasonal signal that the Holt-Winters algorithm can model effectively (Heydari et al., 2019; Sawalha & Al-Naymat, 2025; Swagatika et al., 2023). Unlike neural networks that often require massive datasets to avoid overfitting, this method proves remarkably robust for moderate-sized hydrological time series (N=49), balancing model simplicity with predictive precision (Collados-Lara et al., 2023; Pilz et al., 2019; Sadio et al., 2023).

Based on the forecasting results generated using the Holt-Winters Exponential Smoothing method in Minitab, the forecasted river stage levels for the Bengawan Solo River were obtained for Periods 50 to 60 (corresponding to February to December 2025). Further analysis was conducted by comparing each forecasted value with the flood alert threshold criteria established for the Jurug Observation Station. Further analysis was conducted by comparing forecasted values with flood alert thresholds. The visual comparison between actual data and the forecast is shown in Figure 5.

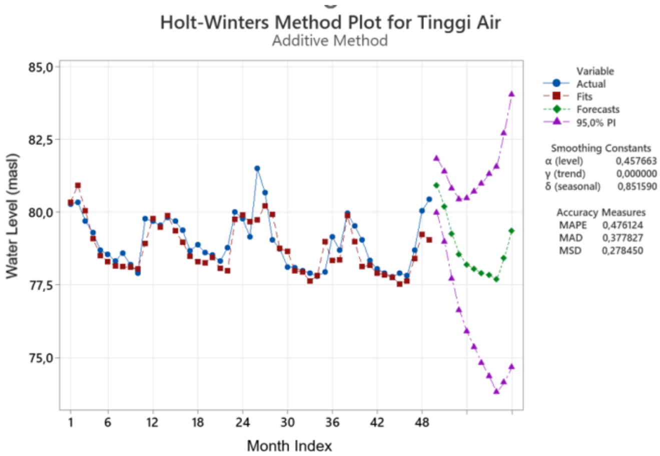

Figure 5. Bengawan Solo river water level forecasting plot

Figure 5 visually confirms that the forecasted trajectory (green line) closely follows the historical seasonal pattern, with confidence intervals (purple) expanding over time. The specific numerical forecast values for the upcoming periods are detailed in Table 8.

Table 8. Bengawan Solo River water level forecast results

Month	Forecast (masl)	Lower Bound (masl)	Upper Bound (masl)	Flood status prediction
February (P-50)	80.8230	79.9046	81.7415	Safe
March (P-51)	80.1132	78.9188	81.3076	Safe
April (P-52)	79.1907	77.6608	80.7205	Safe
May (P-53)	78.4724	76.5789	80.3659	Safe
June (P-54)	78.1331	75.8614	80.4049	Safe
July (P-55)	77.9742	75.3157	80.6327	Safe
August (P-56)	77.8365	74.7860	80.8870	Safe
September (P-57)	77.7728	74.3270	81.2187	Safe
October (P-58)	77.6243	73.7806	81.4679	Safe
November (P-59)	78.3616	74.1185	82.6047	Safe
December (P-60)	79.0951	74.4512	83.7390	Safe

Based on the forecasting results in Table 8, generated using the Holt-Winters Exponential Smoothing method (Lukman & Tanan, 2021; Rentería-Mena & Giraldo, 2024), it was observed that from February to October 2025, the predicted river stage levels of the Bengawan Solo River exhibited a gradual decline, ranging from 80.82 masl to 77.62 masl. These forecasted values remain well below the green alert threshold of 82.98 masl, indicating that river flow conditions during this period are expected to remain stable and within safe limits, with no indication of imminent flooding (Shrestha et al., 2025).

The forecasting results for November–December 2025 reveal a statistically consistent upward trajectory in river water levels, increasing from 78.36 masl to 79.09 masl. Although these values remain below official alert thresholds, the significance of this increase lies not in its absolute magnitude but in its temporal positioning within the hydrological cycle. The upward inflection coincides with the early phase of the Asian Monsoon transition, suggesting that the model successfully captures seasonal hydrodynamic sensitivity rather than merely projecting trend continuation. This indicates that the Additive Holt-Winters framework is responsive to cyclical basin dynamics embedded in the historical series.

This result aligns with findings by Liu et al., (2021) and Putri & Kristianto (2021), who identified progressive soil saturation and enhanced runoff responsiveness during transitional monsoonal phases. Research by Surovyatkina & George (2022) similarly discusses hydrologically unstable transition periods preceding monsoon intensification. However, unlike previous studies that relied primarily on rainfall–runoff simulations or ARIMA-based projections, this study demonstrates that seasonality-driven exponential smoothing alone can adequately represent transitional hydrological escalation patterns in river systems with stable periodic structures. Asri et al., (2023), Adhikari et al., (2024), and Sa'adi et al.,

(2024) emphasize the role of exogenous climatic anomalies such as La Niña in flood amplification, the present findings suggest that baseline seasonal momentum already provides an early structural signal of potential escalation, even before extreme anomalies occur. Thus, the interpretation extends beyond confirmation and indicates that seasonal decomposition may function as a first-layer early warning mechanism in tropical basins.

From a generalization perspective, the findings suggest that for river systems characterized by strong, repetitive annual cycles and relatively stable morphological conditions, parsimonious additive exponential smoothing models, such as Holt-Winters, can yield highly reliable medium-term forecasts (Brito et al., 2021; L. Kumar et al., 2024). These models are effective in capturing seasonal patterns, trends, and variations in water level data, making them valuable tools for river forecasting in stable environments (Papacharalampous & Tyralis, 2020). However, this generalization is bounded to hydrological contexts where structural seasonality dominates stochastic volatility. In highly irregular basins influenced by anthropogenic regulation or erratic precipitation regimes, model performance may differ substantially (Barrow et al., 2020; Patterson et al., 2022). This is because increased noise, outliers, and structural changes, often present in such irregular systems, can severely affect the quality and reliability of exponential smoothing forecasts (Barrow et al., 2020). Shifting streamflow patterns due to climate change and varying underlying surface conditions also pose challenges to models that rely on stable seasonality (Yang et al., 2020; Patterson et al., 2022).

The novelty of this research lies not merely in applying the Additive Holt-Winters model, but in empirically demonstrating that a low-complexity, interpretable statistical model can achieve exceptional predictive precision (MAPE $< 1\%$) within a tropical fluvial system context. Recent hydrological literature increasingly favors machine learning architectures such as Neural Networks or hybrid ARIMA-ML frameworks (Aini et al., 2022; Hunt et al., 2022; Iqbal et al., 2023), often under the assumption that higher algorithmic complexity ensures superior predictive capability. This study challenges that paradigm by evidencing that, in seasonally structured river systems, model interpretability and structural alignment with cyclical hydrology may outweigh computational sophistication. Therefore, the contribution is both methodological and epistemological: it reasserts the relevance of classical time-series decomposition in contemporary hydrological forecasting discourse.

The implications of this research are twofold. Theoretically, it reinforces the argument that hydrological forecasting accuracy depends on structural compatibility between model assumptions and basin characteristics rather than algorithmic complexity alone. Practically, the results provide actionable medium-term foresight for the Bengawan Solo River Basin Center (BBWS) and regional disaster mitigation agencies (BPBD), supporting preventive mitigation strategies consistent with disaster risk reduction frameworks (Mawardi et al., 2021; Salgado & Nájera, 2022; Hakim et al., 2023; Fernández-Nóvoa et al., 2024). The capacity to anticipate gradual seasonal escalation allows for strategic scheduling of infrastructure maintenance and resource allocation during predicted low-level months (August–October), thereby strengthening anticipatory governance in tropical riverine environments.

Despite its strong predictive performance, several limitations must be acknowledged. Methodologically, the model assumes additive seasonality and linear trend continuity, which may underrepresent nonlinear hydrological shocks. The absence of exogenous climatic covariates restricts sensitivity to abrupt extreme-weather disturbances. Additionally, the reliance on historical gauge data may introduce measurement bias or structural breaks not explicitly modeled. Consequently, future research should explore hybrid modeling approaches integrating Holt-Winters smoothing with real-time meteorological predictors such as rainfall intensity, soil moisture indices, and upstream discharge variability. Incorporating anomaly detection frameworks or regime-switching models may also enhance robustness under climate variability scenarios.

CONCLUSION

This study confirms that the additive Holt-Winters Exponential Smoothing method is an effective approach for forecasting seasonal river stage levels in a tropical river system. By utilizing monthly water level data from the Bengawan Solo River, the model was able to capture stable seasonal patterns and generate reliable medium-term forecasts, demonstrating its suitability for hydrological time series characterized by additive seasonality. From a practical perspective, the forecasting framework developed in this study provides meaningful support for flood early warning systems. The ability to produce months-ahead predictions enables decision-makers to move beyond reactive emergency responses toward more proactive flood risk mitigation strategies, including anticipatory infrastructure maintenance and preparedness planning. This is particularly valuable for institutions responsible for river basin management and disaster mitigation in data-limited environments. Despite its strong performance, this study has certain limitations. The Holt-Winters model does not incorporate external hydrological drivers such as rainfall intensity, weather forecasts, or dam operation schedules, which may influence river stage dynamics under extreme conditions. Consequently, forecast accuracy may be reduced during anomalous events that fall outside the model's assumptions. Future research is encouraged to extend this work by integrating exogenous variables, multi-station datasets, or hybrid modeling approaches to enhance predictive robustness and adaptability. Such developments would further strengthen the role of seasonal forecasting models as practical and scalable components of flood early warning systems in tropical riparian regions.

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AUTHOR CONTRIBUTIONS

Indra Jati Mukminan was responsible for collecting and organizing the data, analyzing the data, and writing the manuscript. Laila Fitriana assisted in developing the research design and approved it, supervised the data collection process, and provided critical evaluation of the results and the final manuscript.

CONFLICTS OF INTEREST

The author(s) declare no conflict of interest.

USE OF ARTIFICIAL INTELLIGENCE (AI)-ASSISTED TECHNOLOGY

The authors declare that no artificial intelligence (AI) tools were used in the generation, analysis, or writing of this manuscript. All aspects of the research, including data collection, interpretation, and manuscript preparation, were carried out entirely by the authors without the assistance of AI-based technologies.

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