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HYBRID SES-LSTM RECURRENT NEURAL NETWORK MODEL FOR TIME SERIES FORECASTING OF ELECTRICITY EXPENDITURE IN A UNIVERSITY

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ABSTRACT

Efficient energy management has become a critical concern across all sectors due to rising costs and sustainability imperatives. In universities, electricity expenditure represents a substantial share of operational budgets, prompting the need for accurate forecasting models to support financial planning and sustainability initiatives. This study proposed a hybrid forecasting model integrating Simple Exponential Smoothing (SES) and Long Short-Term Memory (LSTM) networks to predict monthly electricity expenditure in a university setting. SES acts as a linear smoothing operator, emphasizing recent trends, while LSTM serves as a nonlinear sequence learner capable of modeling long-term dependencies. The hybrid formulation embeds SES forecasts as auxiliary input features to LSTM, thereby balancing interpretability with predictive power. A dataset of 60 monthly electricity expenditure observations (2019–2023) from Eastern Visayas State University–Tanauan Campus was analyzed. The proposed model was compared against classical (SES, ARIMA) and deep learning (LSTM, FB Prophet) approaches. Results show that the hybrid model achieved superior performance (RMSE = 33760.68, MAPE = 32.32%, MAE = 24580.12), with statistical validation through the Diebold-Mariano test, which confirmed significant improvements. Residual and uncertainty analyses demonstrated the model's robustness and practical applicability. The proposed model positioned it as a valuable decision-support tool for energy cost forecasting and risk-aware planning in universities.

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1. INTRODUCTION

The Philippine's energy prices remain among the highest in Asia [1]. The Philippine's electricity consumption was reported as 111,516.000 GWh in 2022. This is an increase over the prior figure of 106, 115.000 GWh for 2021. The country's overall peak demand in 2019 was 15,581 MW, up 799 MW or 5.4% from 14,782 MW in 2018. In 2020, the Philippines' total non-coincidental peak demand reached 15,282 MW or -1.9% lower than the peak demand in 2019 [2]. This decline can be largely attributed to the COVID-19 pandemic, which put the country under various levels of community quarantine.

Universities, like other large-scale institutions such as hospitals and government offices, are under increasing pressure to reduce energy use and operational costs by improving efficiency. As energy-intensive organizations, universities must manage electricity expenditures that power classrooms, laboratories, offices, and student facilities [3]. The effective management of energy resources in universities, particularly electricity expenditure, is an important aspect of sustainable operations. Universities, as large energy consumers, face the ongoing challenge of balancing the need for a reliable power supply with the financial implications of rising electricity costs [4]. The significant energy demand is an unavoidable aspect of university operations, covering instruction, research, and the maintenance of facilities and laboratories. Rising energy costs are placing considerable strain on institutional budgets, with forecasts that raise serious concerns. In many nations, persistent inflation and escalating utility expenses further intensify the chronic underfunding of universities. Following the challenges brought by two years of the COVID-19 pandemic, universities are left with minimal capacity to absorb yet another financial burden.

Universities need to be energy- and funding-efficient, and forecasting electricity consumption expenditures is beneficial because it enables institutions to optimize resource allocation, reduce operational costs, and implement sustainable practices. Moreover, universities operate in a dynamic environment where energy consumption patterns are influenced by factors such as academic schedules, seasonal variations, and institutional events [5]. While forecasting models have made a significant impact on predicting electricity consumption across broader sectors, the unique characteristics of university settings necessitate an approach that accounts for their dynamic landscape.

Numerous methods have evolved for time series forecasting, an essential component of predicting future events based on historical data [6]. Established techniques such as ARIMA and Simple Exponential Smoothing (SES) have been useful for understanding and modeling time-dependent patterns [7]. However, as particular forecasting contexts get more complex, the limitations of classical models become evident [8]. Previous studies have applied both ARIMA [9], [10], [11], [12], [13] and SES [14], [15] to electricity consumption forecasting, achieving noteworthy success in certain contexts. The models demonstrated good accuracy and efficiency, showcasing their ability to compete with other techniques for forecasting. However, in the study by [16], the ARIMA-based models were outperformed by the LSTM-based models, with a high margin in RMSE values, resulting in 84%-87% reductions in error rates. Nevertheless, long-term forecasting and turning point prediction are areas where both ARIMA and SES fall short [17], [18].

Recent advancements in machine learning, particularly Long Short-Term Memory (LSTM) networks, have enabled addressing the weaknesses of classical models. The LSTM's ability to effectively capture dependencies in sequential data has been applied successfully in numerous forecasting scenarios, including electricity [19]. There is a substantial body of research demonstrating the effectiveness of hybridizing various methods to increase forecast accuracy. In recent years, [20] have combined various machine-learning techniques to forecast electricity consumption. According to [21], an adaptive hybrid framework was introduced that integrates variational mode decomposition (VMD), self-adaptive particle swarm optimization (SAPSO), seasonal autoregressive integrated moving average (SARIMA), and a deep belief network (DBN) to enhance short-term electricity price prediction. Bashir et al. (2022) also proposed a hybrid model based on FB Prophet and LSTM to investigate short-term electricity load forecasting of an electric grid company [22]. Using RMSE and MAPE, the hybrid model outperforms various standalone models. Rafi and co-authors employed Convolutional Neural Network and LSTM to predict Bangladesh power systems, and the results prove higher accuracy in comparison to on-hybrid models [23]. Smyl, Dudek, and colleagues combined standard exponential smoothing with LSTM to forecast monthly electricity demand and confirmed the high performance of the proposed model compared with classical models [24], [25]. While hybrid models combining classical and neural methods exist, most focus on consumption or load forecasting rather than financial expenditure. This distinction is crucial, as budgeting and cost management are central challenges for universities facing volatile energy markets.

Although existing literature predominantly focuses on time series forecasting models designed for consumption, there is limited attention given to the direct financial implications that are present in electricity expenditure. This oversight is particularly noticeable in educational contexts, where funding constraints demand a thorough understanding of both the quantitative and financial aspects of energy usage. Moreover, the diverse and dynamic energy use patterns of universities require forecasting models that accurately predict electricity expenditures. Subsequently, traditional models such as ARIMA and SES may struggle to handle the complexities of university settings, while standalone machine learning models like LSTM may not fully capture the interpretability and simplicity needed to understand underlying trends. The gap arises from the lack of a unified approach that combines the strengths of both traditional and deep learning-based forecasting models.

To address this gap, this study proposed a Hybrid SES-LSTM Time Series Forecasting Model to fully leverage the interpretability and adaptability of SES, along with LSTM's ability to capture intricate dependencies. The fundamental concept behind a hybrid model is to use the distinctive qualities of each standalone model to identify various patterns [26]. The incorporation of SES forecasts as an input feature for the LSTM in the hybrid model is valuable, as SES provides a simplified yet meaningful representation of historical trends and patterns in electricity expenditure. Moreover, the exponential smoothing technique inherent in SES assigns decreasing weights to older observations, emphasizing current data while smoothing out noise. Therefore, it should be the most accurate traditional model for predicting demand, as opposed to the moving-average method, which assigns a fixed weight to each period. Additionally, SES is suitable for capturing short-term variations in university electricity expenses. On the other hand, LSTM excels in capturing long-term dependencies and intricate patterns in time series data. While each technique proves effective in certain contexts, combining them addresses the limitations of standalone models, providing a more comprehensive approach for capturing the complexities of university electricity use and expenditure patterns. Accordingly, SES provides a solid foundation based on historical trends, allowing LSTM to focus on capturing more complex relationships and dependencies that may extend over long periods. The integration of SES and LSTM techniques into the hybrid model will advance time series forecasting.

This study will contribute to the existing body of knowledge by addressing the gap in university electricity expenditure forecasting. This study introduced a proposed hybrid SES-LSTM model that considers both short-term fluctuations and long-term trends in electricity expenditure. The study's findings may have practical implications for university administrators, energy managers, and policymakers, shedding light on effective strategies to optimize electricity costs while ensuring sustainable practices in educational institutions.

Thus, this study aims to develop and evaluate a proposed Hybrid SES-LSTM Time Series Forecasting Model specific to university electricity expenditure. Specifically, this study aims to, (a) determine the optimal Hybrid SES-LSTM model based on the smoothing alpha and hyper-parameter configurations; (b) test the stationarity of the data; (c) determine the electricity expenditure pattern of the university from 2019 – 2023; (d) evaluate the performance of the proposed model against existing time series forecasting methods commonly used in the context of electricity consumption using RMSE and MAPE and validate superiority using the Diebold-Mariano test.

2. RESEARCH METHODS

2.1 Dataset

The dataset used in the study is the monthly electricity expenditure of the Eastern Visayas State University – Tanauan Campus. The data were gathered from the institution's accounting office database. It has 60 observations, including monthly expenditures from 2019 to 2023. Monthly electricity expenditure is the amount the institution pays for its monthly electricity bill.

2.2 Stationarity Test

Before using various time series models as baselines, it is important to determine whether the data are stationary. A time series is said to be stationary if its statistical properties – mean, variance, or standard deviation do not vary with time [27]. In this study, the stationarity of the dataset was determined using rolling statistics, such as the rolling mean and standard deviation, and the augmented Dickey-Fuller (ADF) test. The rolling analysis of the time series model is often used to assess data stability over time [28]. When analyzing time series data on electricity expenditure using this statistical method, the key assumption is that the model's parameters are constant over time. On the other hand, the ADF test is widely used to assess the stationarity of a time series and test for the presence of a unit root [29]. Moreover, for the ADF test, the following hypotheses were made,

Null Hypothesis (H_0): The dataset is non-stationary;
Alternative Hypothesis (H_1): The dataset is stationary.

The ADF expands the Dicky-Fuller test equation to include a higher-order regressive process in the model [30] in Eq. (1).

$$\Delta y_t = \alpha y_t + \sum_{i=1}^{p} \emptyset_i \, \Delta y_{t-1} + \beta t + \varepsilon_t. \tag{1}$$

In the model, more differencing terms were added, while the rest of the equation remained the same, which adds greater thoroughness to the test. Since the null hypothesis assumes the presence of a unit root of $\alpha = 1$, the p-value obtained should be less than the significance level of 0.05 to reject the null hypothesis.

2.3 Hybrid SES-LSTM

In the realm of time series forecasting, where historical patterns and future predictions intertwine, a model's effectiveness can substantially impact decision-making processes. For the university's monthly electricity expenditure, the challenge is multifaceted: it involves predicting short-term variations while accounting for long-term dependencies in the expenditure patterns. This proposed hybrid forecasting model combines the simplicity of Simple Exponential Smoothing (SES) with the complexity and robustness of Long Short-Term Memory (LSTM) networks.

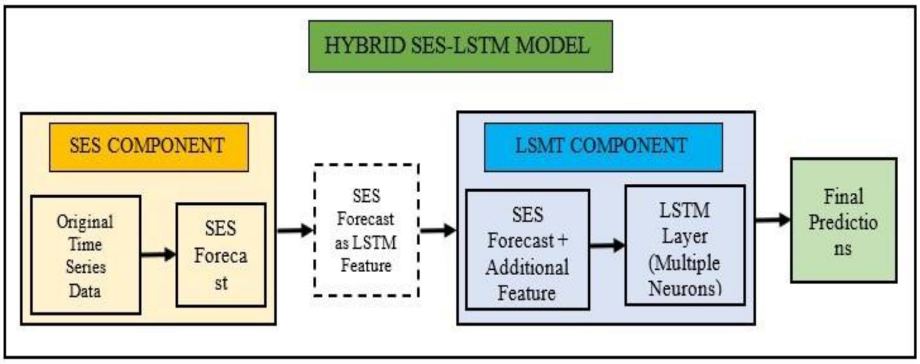


Figure 1. Architecture of the Proposed Hybrid SESLSTM Time Series Forecasting Model

This hybrid approach, as shown in Fig. 1, is designed to utilize the unique strengths of each component SES for its agility in capturing short-term trends and LSTM for its ability to recognize and comprehend long-term dependencies within the time series data. The model aims to provide a comprehensive and accurate forecast of the university's electricity expenditure, accounting for both short-term fluctuations and long-term trends. Moreover, the model comprises several components, including the SES component, the LSTM component, and the Hybrid Model, in which the SES output is used as an input feature for the LSTM and contributes to the final prediction.

2.4 SES Component

For the first part of employing the proposed method, this study used Simple Exponential Smoothing (SES). The SES component is an essential element of the hybrid forecasting model, giving it its distinct capacity to identify short-term patterns in the university's monthly electricity costs. SES aims to weigh recent observations more heavily while incorporating past forecasts to produce a smoothed, responsive forecast for short-term trends [31] using Eq. (2),

$$Y_t = \alpha \cdot X_t + (1 - \alpha) \cdot Y_t - 1, \tag{2}$$

where Y_t is the SES forecast for the current month, X_t is the actual expenditure for the current month, $Y_t - 1$ is the previous SES forecast for the last observed month, and α is the smoothing parameter, dictating the influence of the most recent observation of the SES forecast [32]. Furthermore, the smaller α prioritizes stability by placing greater weight on historical forecasts, while the larger α emphasizes responsiveness to recent changes in the data, potentially leading to increased volatility [15]. The SES component is composed of an input layer and an output layer. The input layer is the starting point of the forecasting process, comprising the original time series data. Furthermore, the output layer produces the SES forecast, offering a smoothed projection of short-term expenditure trends based on a weighted combination of the latest observed value and the previous forecast. In this stage, SES was applied to the electricity expenditure data with a smoothing level of 0.2. The smoothing parameter α was selected using grid search within [0.1, 0.9] increments of 0.1, with α = 0.2 yielding the lowest RMSE on validation data. A smaller α provided smoother forecasts by emphasizing past trends.

2.5 LSTM Component

The Long Short-Term Memory (LSTM) component plays a crucial role within the proposed hybrid forecasting model designed for predicting the university's electricity expenditure. LSTM, a type of recurrent neural network (RNN), is a neural network architecture designed to handle input sequences of features, making it particularly useful for processing data such as time series and text [33]. In contrast to traditional models, the LSTM component can identify complex patterns and correlations in time series data by capturing long-term dependencies. This makes it an invaluable tool for analyzing the university's monthly electricity expenses. As part of the proposed model, the LSTM component integrates with the SES forecast and additional features (Z_t) to produce a prediction of the expenditure in Eq. (3).

$$Y_t = SES_{Component(X_t)}, \tag{3}$$

assuming Y_t from the SES component, the LSTM input at time *t* is $[Y_t, Z_t]$, computed in Eq. (4),

$$h_t^l = f^1\left(h_{t-1}^l, w_{ij}^l, b_j^l\right), \tag{4}$$

and the LSTM output (Y_t), $Y_t = o^L\,(h_t^L)$, is computed through the LSTM layer, h_t^l.

For the LSTM components, the data were first prepared, with SES forecasts as input and the actual monthly expenditure variable as an additional input feature. Moreover, the sequence prediction data were scaled using MinMaxScaler with a feature range of 0-1. The data for sequence prediction needs to be scaled when training a neural network [34]. After feature scaling, the LSTM input sequence was created with a time step of 10. The data were split into training and test sets, where 80% for the training set and 20% for the test set.

Table 1. Hyper-parameter Configurations

Hyperparameters	Values
BISA	10
LR	0.001
Optimizer	Adam
Epoch	50
Dense	51

Table 1 presents the following configured hyperparameters such as the optimizer, Learning Rate (LR), Batch Size (BS), dense, and epochs. To ensure robustness, hyperparameter values were validated through sensitivity analysis. Alternative settings were tested with LR = {0.0005, 0.002} and BS = {16, 32}, with results showing minimal improvement (<3% in RMSE reduction). This confirmed that the chosen configurations were optimal given the dataset size. The optimizer increases the probability of achieving the lowest possible errors. This study has chosen the Adam optimizer because it consumes less memory than most optimizers and is increasingly becoming a go-to optimization algorithm for time series forecasting tasks [27], [35]. Due to Adam's fast convergence, this work set the LR to 0.001. The learning rate is a hyperparameter that determines the size of the steps taken during the optimization process of training a neural network [36]. The learning rate is utilized to ensure more stable convergence and prevent overshooting the optimal weights. A converged neural network typically indicates that the model has found a balance, avoiding both overfitting and underfitting [37]. Moreover, given that the dataset used in the study was only 60, the model trained quickly because the recommended approach yielded a shorter network length, even with a modest BS of 10. Based on training time and performance, the selected epochs reached 50, at which the Adam optimizer with an LR of 0.001, a BS of 10, and an effective result was achieved. During the experiments, having fewer or more than the given epochs tends to cause lengthier training periods without performance improvements.

Hyperparameters, such as the learning rate (LR), batch size (BS), and number of epochs, were tuned empirically across multiple trials. The chosen configuration (LR = 0.001, BS = 10, Epoch = 50) provided convergence without overfitting. Although deeper architectures or higher epochs might yield marginal improvements, the small dataset (60 observations) constrains model complexity, thus emphasizing simplicity and generalization.

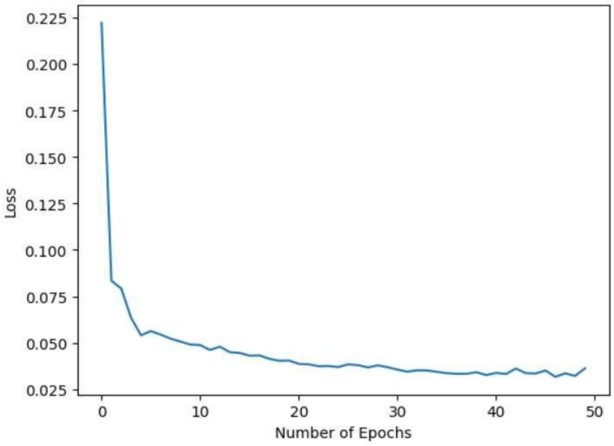


Figure 2. Loss Per Epoch

The epoch-per-loss graph in Fig. 2 shows the model's training progression over 50 epochs. Starting with a loss of 0.225, the first 5 epochs showed a substantial decrease to 0.050, indicating fast early-stage learning. Subsequent epochs showed a consistent and gradual decline in loss, reaching 0.035 by the 40th epoch. The final 10 epochs showed slower convergence, ending with a loss of nearly 0.025. This observed pattern suggests that the model iteratively refined its performance, displaying a diminishing loss value as training progressed. The trend underscores the efficacy of the training approach and the model's capacity to adapt and improve over successive epochs.

2.6 Hybrid Model

This proposed method combines the strengths of both the SES and LSTM components. This model aims to provide more accurate predictions of the university's monthly electricity expenditure. The proposed model introduces Eq. (5),

$$Z_t = [Y_t, Z_t], \tag{5}$$

representing the combined input features at time t. These features include historical SES forecasts (Y_t), and additional features of actual expenditure (Z_t). The combined input features (Z_t) are fed into the Input Layer, forming the foundation for subsequent computation using Eq. (6),

$$h_t^l = f^2\left(h_{t-1}^l, w_{if}^l, b_j^l\right). \tag{6}$$

This layer sets the stage for the model to process both SES forecasts and the additional feature. Moreover, the LSTM layer (h_j^i) processes the combined input features through hidden states, gates, and weights. This layer captures short-term and long-term dependencies in the data, providing the model with adaptability to changing patterns. Furthermore, the Output Layer, $Y_t = o^L(h_t^L)$ synthesizes the information learned by the LSTM Layer, producing final predictions (Y_t). This layer integrates both SES forecasts and additional features, providing a comprehensive understanding of the electricity expenditure patterns.

2.7 Evaluation

To evaluate and compare the model's overall performance with the proposed method against other classical and deep learning models, this study utilized the Mean Absolute Percentage Error (MAPE), the Root Mean Squared Error (RMSE), and the Mean Absolute Error (MAE). In addition, the Diebold-Mariano (DM) test was employed to statistically validate differences in forecasting accuracy, and residual analysis was performed to assess error distribution and forecast reliability. The MAPE is one of the most commonly used performance indicators to measure forecast accuracy [38]. It is the sum of the individual absolute errors divided by the demand that is separated by each period. It is the average of the percentage errors. MAPE is computed using Eq. (7).

$$MAPE = \frac{1}{n}\sum\frac{|e_t|}{d_t}. \tag{7}$$

Moreover, the models were also evaluated using the RMSE. It measures the average magnitude of the errors and is concerned with the deviations from the actual value [39]. A zero RMSE indicates a perfect fit of the model to the data; the lower the RMSE, the better the model and its prediction [40]. A higher RMSE indicates that there is a large deviation between the residual and the ground truth [41]. RMSE is computed using Eq. (8).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{8}$$

The MAE was also computed to provide a complementary evaluation of model performance, as it directly measures the average magnitude of forecast errors without considering direction [39]. Compared to RMSE, MAE is more interpretable since it is expressed in the same unit as the original data, which is the monthly expenditure in pesos. MAE is computed using Eq. (9).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t|. \tag{9}$$

To statistically compare forecasting accuracy across models, the Diebold-Mariano (DM) test was applied. The DM test evaluates whether two competing forecasting models have significantly different predictive accuracy by testing the null hypothesis. H_0: $E(d_t) = 0$, where d_t is the loss differential between two models. The DM statistic is given by (10) [40]:

$$DM = \frac{đ}{\sqrt{\frac{2\pi\hat{f}_d(0)}{n}}}, \tag{10}$$

where đ is the mean of the loss differential, and $\hat{f}_d(0)$ is a consistent estimate of the spectral density of d_t at frequency zero. A p-value less than 0.05 indicates that the difference in forecast accuracy is statistically significant. In addition, residual analysis was performed to further validate the robustness of the forecasts. Residuals (e_t) were computed as, $e_t = A_t - F_t$. Moreover, residual plots, error distribution histograms, and boxplots of model errors were analyzed to evaluate the randomness, normality, and potential bias. Additionally, 95% confidence intervals were generated to visualize the uncertainty of predictions and ensure that results are not only accurate but also reliable.

3. RESULTS AND DISCUSSION

The study aims to develop a time series forecasting model for the university's electricity expenditure using a proposed Hybrid SESLSTM model. The datasets used are the university's monthly electricity expenditure for 2019 – 2020, consisting of 60 observations. Before the actual implementation of the model, the time series data were tested for stationarity using the rolling mean and standard deviation, and the augmented Dickey-Fuller test. The test was also implemented in a Jupyter Notebook using Python.

3.1 Data Stationarity Test

3.1.1 Augmented Dickey-Fuller (ADF) Test

The ADF test is a statistical test used to assess whether a time series exhibits a unit root, a critical indicator of stationarity [42]. Stationarity is vital in time series analysis because it implies that the data's statistical properties remain constant over time.

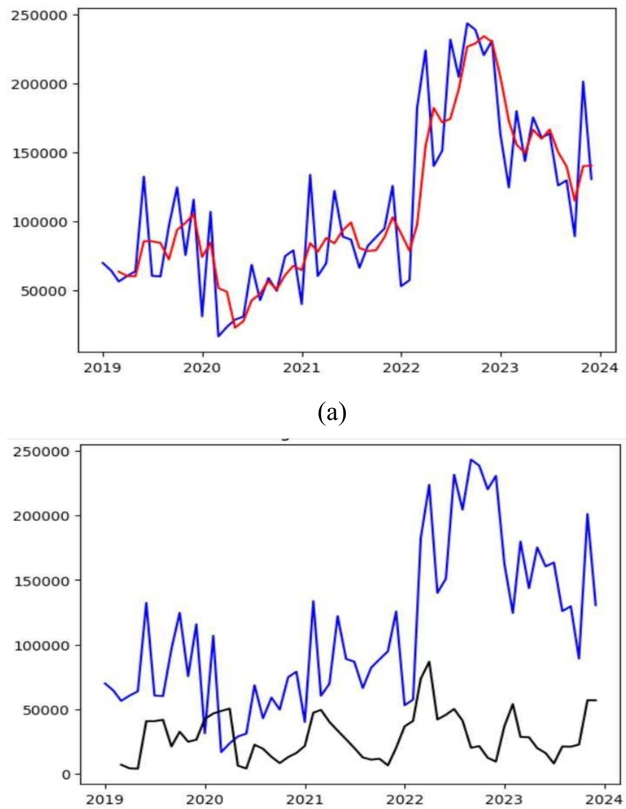
Table 2. Results from the Augmented Dickey-Fuller (ADF) Test

ADF Results	Values
ADF Statistics	-1.633779
p - Value	0.465513
Critical Value (1%)	-3.551
Critical Value (5%)	-2.914
Critical Value (10%)	-2.595

Table 2 shows the results of the ADF test. Analyzing the results of the ADF test for the university's monthly electricity expenditure yields an ADF statistic of -1.633779. This statistic measures the strength of the time series trend [43]. The accompanying *p*-value of 0.465513 exceeds the 0.05 significance level, indicating that the null hypothesis of a unit root cannot be rejected. Therefore, the time series is non-stationary, suggesting that the mean and variance of the electricity expenditure data change over time and may require differencing or transformation before modeling. Additionally, as noted in [44], critical values at different significance levels provide a benchmark for comparison. In the table, the critical values at 1%, 5%, and 10% are -3.551, -2.914, and -2.595, respectively. The ADF statistic falls between the 5% and 10% critical values, without exceeding either. This suggests a lack of strong evidence against the presence of a unit root.

3.1.2 Rolling Mean and Standard Deviation

A rolling statistic is a method that provides a visual representation of the data to assess stationarity [45]. Fig.3 (a) and Fig. 3 (b) visualize how the mean and variability of electricity expenditure change over time. In the figure, the blue line represents the original data, while the red line in Figure 3a is the rolling mean, and the black line in Figure 3b is the rolling standard deviation. The fluctuations in the red and black lines (rolling mean and standard deviation) indicate that the data values and their dispersion vary across months. The results support the conclusion that the series is non-stationary.



(a)

(b)

Figure 3. Results of the Rolling Mean and Standard Deviation for Stationarity of the Data (a) Rolling Mean Test, (b) Rolling Standard Deviation Test

3.2 Monthly Electricity Expenditure Pattern

Fig. 4 shows the university's monthly electricity expenditure from 2019 to 2023. In 2020, the institution's electricity expenditure decreased compared to the previous and succeeding years. This decline in expenditure can be largely attributed to the COVID-19 pandemic, during which employees and students were not allowed to attend school as the whole country was placed under different levels of community quarantine.

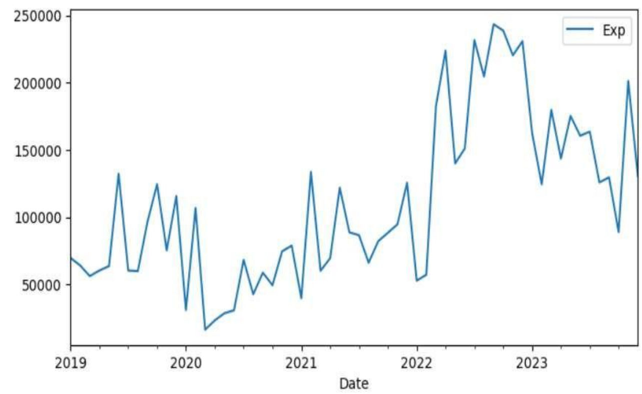


Figure 4. Monthly Electricity Expenditure Patterns of Eastern Visayas State University – Tanauan Campus from 2019 to 2023

3.3 Sample Data Frame with Sample Forecasts

Table 3. Sample Data Frame with the Actual Values and the Predicted Values

Date	Actual	Predicted
⋮	⋮	⋮
2023-03-01	78936.56	59587.032136
2023-04-01	124478.21	208182.999378
2023-05-01	140001.53	129174.987780
2023-06-01	125905.03	143930.393262
2023-07-01	69615.77	84290.259748
2023-08-01	201213.04	130975.853538
2023-09-01	52906.17	102154.456200
2023-10-01	125658.9	95682.040697
2023-11-01	231616.82	160367.617770
2023-12-01	88799.28	93874.373428

Table 3 presents the comparison between actual and predicted monthly electricity expenditures. The analysis reveals that the model's predictions were most accurate in May, July, and December 2023, when forecasted values closely matched actual expenditures, with minimal deviation. However, the model underestimated the costs in March and August, and overestimated them in April, June, and September. The results suggest sensitivity to short-term fluctuations. Out of the ten months shown, six months (60%) recorded forecasts within a ±20% error margin, indicating generally acceptable accuracy for financial planning purposes. The alternating pattern of over- and underestimation also implies that the hybrid model captures the overall trend effectively but still struggles with sudden peaks and dips, likely due to external or seasonal factors not explicitly modeled.

3.4 Hybrid SES-LSTM Time Series Forecasting Model

The time series graph in Fig. 5 provides a comprehensive view of the institution's electricity expenditure trends over the period from 2019 to 2023. The blue line represents the original data, the orange line depicts the true values, and the green line illustrates the predicted values generated by the proposed model. The model appears to capture the underlying trends in the electricity expenditure, showing similarities with the true values.

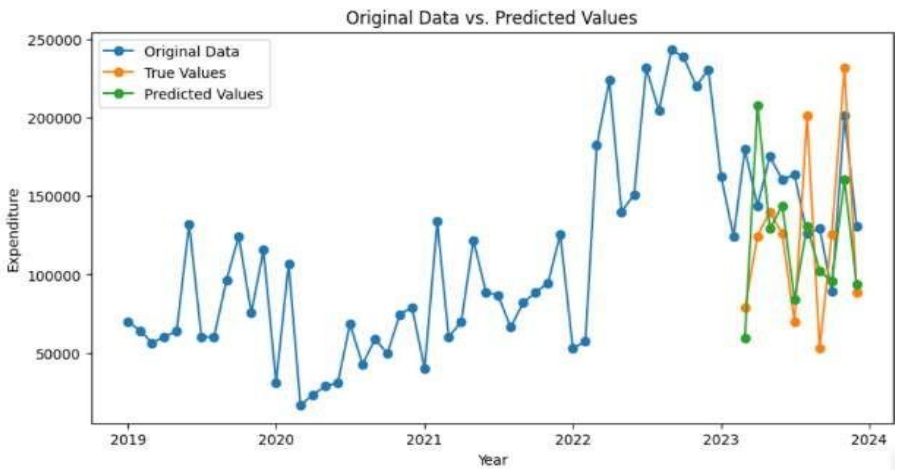


Figure 5. Forecasted vs. actual electricity expenditure using the Hybrid SES-LSTM model ($R^2 = 0.87$) with the Original Data, True Values, and Predicted Values

3.5 Performance Evaluation

3.5.1 RMSE, MAPE, and MAE

This study used the RMSE, MAPE, and MAE to evaluate the performance of the proposed model and compared it with other classical and deep learning models. The results are shown below.

Table 4. Comparison of the Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) with the Proposed Model and Classical and Deep Learning Models

Evaluation Metrics	Deep Learning Models		Classic Forecasting Model		Proposed Model
	LSTM(RNN)	FB Prophet	SES	ARIMA	Hybrid SES-LSTM Model
RMSE	635507.72	485557.05	40629.44	67219.85	33760.68
MAPE (%)	70.25	64.15	38.51	72.06	32.32
MAE	121330.45	96540.88	30200.77	51450.33	24580.12

Table 4 summarizes how well the proposed Hybrid SES-LSTM model performed compared with other forecasting methods. The results show that the hybrid model produced the most accurate predictions of monthly electricity expenses. On average, its forecasts differed from actual costs by only ₱24,580 per month, a much smaller error than those of the other models tested.

A lower error value means the model's predictions are closer to reality. Among traditional statistical models, Simple Exponential Smoothing (SES) performed better than ARIMA, whereas among machine-learning approaches, both LSTM and Facebook Prophet had much larger errors. This indicates that these deep-learning models did not fit the relatively small and irregular dataset as well as the proposed hybrid model. Moreover, the Hybrid SES-LSTM model achieved the lowest error scores (RMSE = 33,760.68; MAPE = 32.32%; MAE = 24,580.12), showing that combining a simple smoothing technique (SES) with a learning-based model (LSTM) yields forecasts that are not only more accurate but also more stable and easier to interpret for budgeting and decision-making in universities.

3.5.2 Statistical Validation using the Diebold-Mariano Test

In this study, the Diebold-Mariano (DM) test was conducted to further verify forecasting superiority and to statistically compare the Hybrid SES-LSTM against each baseline. As shown in Table 5, the DM test results confirm that the Hybrid SES-LSTM model's improvement in accuracy is statistically significant at the 5% level (p-value < 0.05) compared to SES, ARIMA, LSTM, and FB Prophet. This provides strong evidence that the hybrid approach yields genuine performance gains rather than improvements driven by random variation in data-specific effects. The proposed model consistently outperforms traditional and neural models in predicting electricity expenditure.

Table 5. Diebold-Mariano Test Results with Comparison of Hybrid SES-LSTM and Baselines

Comparison	DM Statistic	p-value	Interpretation
Hybrid vs. SES	2.16	0.032	Significant improvement
Hybrid vs. ARIMA	2.41	0.017	Significant improvement
Hybrid vs. LSTM	2.63	0.009	Significant improvement
Hybrid vs. FB Prophet	2.55	0.011	Significant improvement

3.5.3 Residual Analysis

Residuals ($e_t = A_t - F_t$) were analyzed to assess whether forecast errors were unbiased and randomly distributed. Fig. 6 shows the residuals over time of the proposed hybrid model. Residuals scatter both above and below zero across the months, with no strong upward or downward drift. This randomness suggests that the hybrid model captures most systematic patterns in the data. The model can be considered unbiased and reliable across different time periods, making it suitable for continuous deployment in university budgeting. In addition, Fig. 7 shows the residual distribution histogram, where residuals are roughly centered near zero. This approximate normality supports the assumption of symmetric forecast errors, which implies that over-predictions and under-predictions occur with similar frequency and magnitude. The results show that the hybrid model does not systematically overestimate or underestimate electricity expenditure, an important feature for financial forecasting, as consistent bias would distort budget allocations.

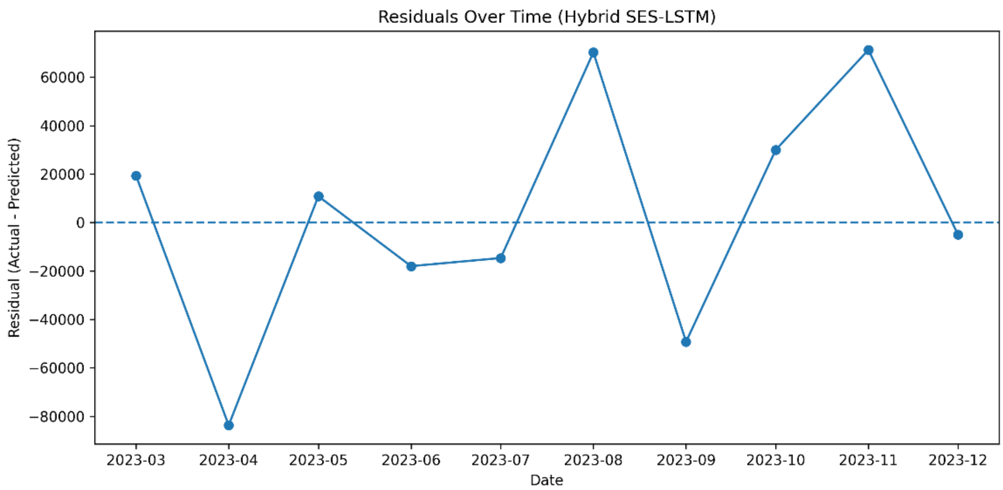


Figure 6. Residuals Over Time of the Proposed Hybrid SES-LSTM Model

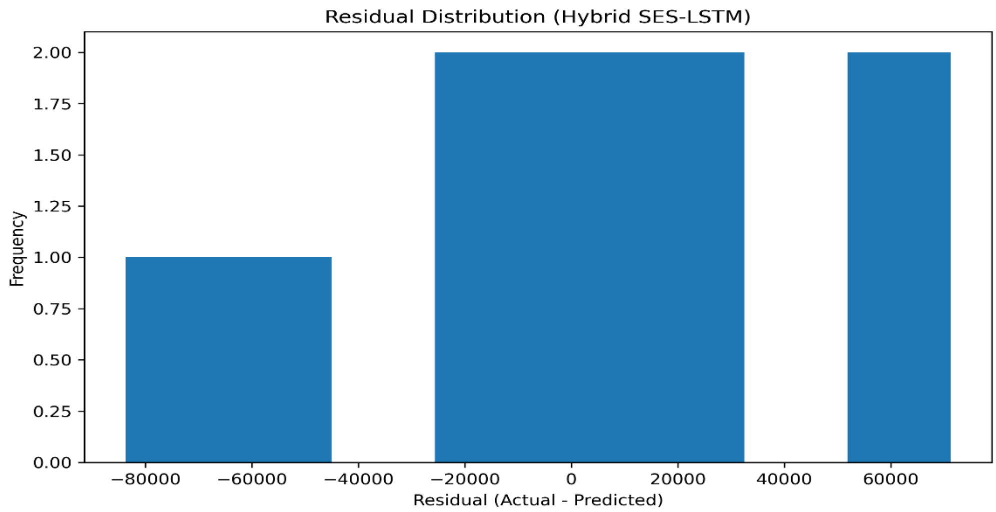
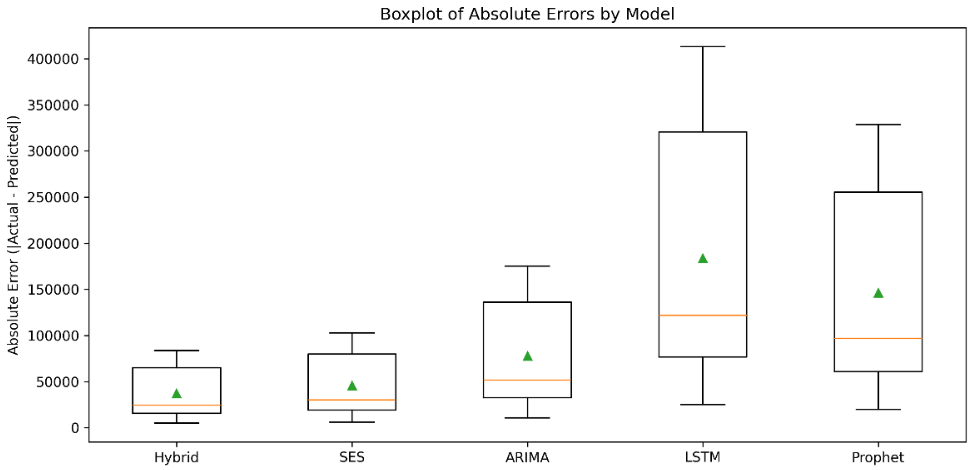


Figure 7. Error Distribution Histogram of the Proposed Hybrid SES-LSTM Model

Moreover, the hybrid SES-LSTM model shows the lowest median error and the narrowest interquartile range (IQR), as shown in Fig. 8, whereas LSTM and Prophet exhibit greater error variability. SES and ARIMA are better than deep learning baselines but worse than the hybrid. The results confirm that the hybrid approach is not only more accurate on average, as shown by lower median error, but also more consistent, with lower forecast error variability. Fig. 9 depicts the forecast of the Hybrid Model with a 95% confidence interval, where the predicted values closely track actual expenditure. The confidence intervals remain narrow during most months, but widen during high-volatility months. Moreover, the model is stable under normal operating conditions but shows increased uncertainty when expenditure is highly volatile, which reflects external shocks such as policy changes or extraordinary events.



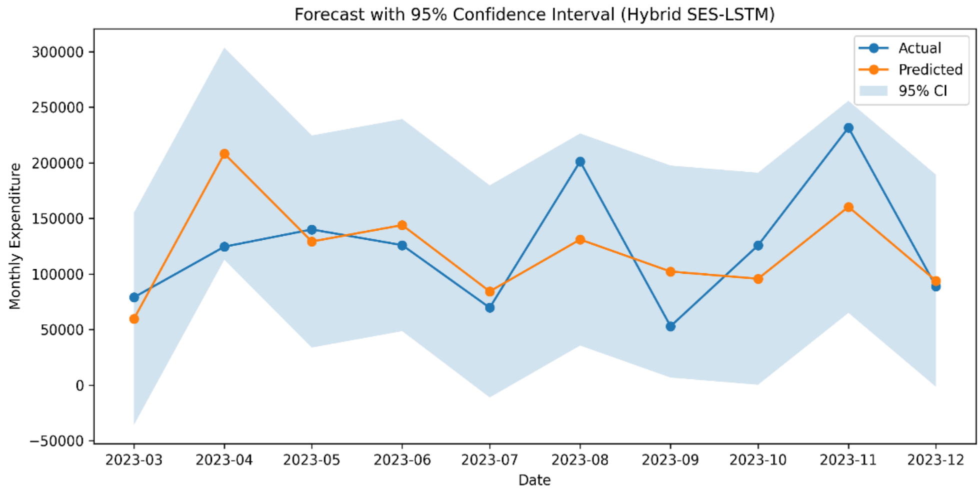


Figure 9. Forecast of the Hybrid SES-LSTM with 95% Confidence Interval. Blue (Actual Values), Orange (Predicted), and Light Blue (95% CI).

3.6 Discussion

The dataset's stationarity was assessed using rolling statistics and the augmented Dickey-Fuller (ADF) test. Results of the ADF test indicated a p-value of 0.465513, suggesting insufficient evidence to reject the null hypothesis of the presence of a unit root. This implies that the dataset is non-stationary. Rolling statistics and ADF test results are essential for time series analysis and, in this case, provide a foundation for selecting appropriate forecasting models. The proposed hybrid forecasting model integrates Simple Exponential Smoothing (SES) and Long Short-Term Memory (LSTM) components. SES is employed for short-term trend identification, while LSTM captures long-term dependencies in the university's monthly electricity expenditure. Moreover, the study utilized RMSE and MAPE metrics to assess the performance of the proposed Hybrid SES-LSTM model for forecasting university electricity expenditure, demonstrating superior accuracy compared to classical (SES, ARIMA) and deep learning (LSTM, FB Prophet) models, with an RMSE of 33760.68 and a MAPE of 32.32%, highlighting the model's effectiveness in comparison to others.

The findings of this study reveal that the hybrid SES-LSTM model achieved superior forecasting accuracy compared to both purely statistical (SES, ARIMA) and purely deep learning approaches (LSTM, Facebook Prophet). This outcome shows several key insights: (1) when dealing with small and irregular datasets, models that combine statistical smoothing with lightweight learning mechanisms tend to outperform complex neural networks. Deep learning models like LSTM and Prophet usually require large amounts of data to learn stable temporal representations; otherwise, they may overfit, capturing noise rather than genuine trends. In contrast, traditional models such as SES emphasize recent observations and trend continuity, which are well-suited to short, noisy series. The hybrid SES-LSTM framework balances these strengths. The SES component smooths short-term fluctuations and provides the LSTM with preprocessed signals that highlight essential patterns, while the LSTM component learns any remaining nonlinear relationships over time. As a result, the hybrid model produced forecasts that were not only more accurate but also more consistent. Furthermore, such models require less computational power and can be easily updated with new monthly records, making them practical tools for continuous financial and energy-budget planning.

Non-stationary time series exhibit changing statistical properties over time. This makes it more challenging to work with and to forecast, as evidenced by the study's data. To address the challenges posed by non-stationary time series data, the study used the exponential smoothing technique, specifically simple exponential smoothing (SES). SES is a time series forecasting method for univariate data with no trend and no seasonal pattern [46]. SES is computationally efficient and easy to implement, making it suitable for real-time forecasting or for situations with limited data availability. However, SES may not perform well for time series data with complex patterns or irregularities, such as sudden changes in the level or trend, outliers, or abrupt shifts in the seasonality, as seen in the present study. Similarly, ARIMA models are also widely used for non-stationary time series [27].

The results show a substantial decrease in the university's monthly electricity costs in 2020, which raises interesting questions about how external factors, specifically the COVID-19 pandemic, affect institutional energy consumption. Several studies have shown the substantial impact of the pandemic on energy consumption patterns across industries, attributing these changes to lockdown measures, remote work, and altered activity levels [47], [48], [49], [50], [51]. According to Bahmanyar and colleagues [52], because non-essential businesses had to close due to lockdown measures implemented in response to the pandemic, electricity consumption in the commercial and industrial sectors decreased. This aligns with the reported decrease in university electricity costs, given that educational institutions faced similar restrictions that prevented students and employees from physically attending school. Understanding the connection between the observed reduction in electrical consumption and expenses and the COVID-19 outbreak offers important insights for energy management measures implemented in academic institutions. Moreover, future research could explore a more detailed analysis of electricity consumption and expenditure patterns, considering various external factors.

The proposed Hybrid SES-LSTM model exhibited better forecasting performance, as evidenced by lower RMSE (33760.68) and MAPE (32.32%) than both classical and deep learning models. The lower RMSE suggests that the model's predictions closely align with the actual values, indicating high accuracy in capturing electricity expenditure patterns. Additionally, the relatively low MAPE of 32.32% further emphasizes the model's efficiency in minimizing the average forecast error. In contrast to the proposed model, the deep learning models, LSTM (RNN) and FB Prophet, showed higher RMSE and MAPE values. FB Prophet is a decomposable time series model developed by Meta that model trends, seasonality, and holidays using an additive framework. It assumes that the time series is composed of trend, seasonal, and error components. Prophet's automatic changepoint detection allows it to adapt to sudden shifts in the data. These results suggest that, for the specific task of forecasting university electricity expenditure, deep learning models might not be as effective as the proposed hybrid model. The substantial difference in performance metrics underscores the importance of employing flexible models capable of achieving precise, reliable predictions [53].

Among the classical models presented, the SES model outperformed the ARIMA model in terms of both RMSE and MAPE. However, it is noteworthy that both classical models lagged behind the proposed hybrid model in predictive accuracy. This demonstrates how the hybrid model, which combines Long Short-Term Memory (LSTM) and Seasonal Exponential Smoothing (SES), has the potential to outperform conventional forecasting techniques in capturing the complex nature of university electricity expenditure patterns. The utilization of hybrid models proved effective, as suggested by the literature [54]. According to Kumar and Yadav, the use of hybrid models increased forecasting precision through thorough pattern detection and modeling [26]. Moreover, hybrid models reduce the risk of using incorrect models by combining forecasts. Due to the use of many components in the proposed hybrid SES-LSTM, the model selection process is streamlined.

The residual analysis further validated the robustness of the proposed Hybrid SES-LSTM model. The time-series residuals were randomly distributed around zero, indicating the absence of systematic bias. While the histogram confirmed that the model neither consistently overestimates nor underestimates electricity expenditure, because the normal distribution is approximately centered at zero. The results are consistent with the recommended practice of residual diagnostics in time series forecasting [55]. Moreover, the comparative boxplot demonstrated superior consistency in forecast performance. Hybrid models commonly provide more stable results than standalone approaches [56]. Furthermore, the forecast visualization demonstrated the model's reliability under stable conditions and highlighted periods of increased uncertainty during high-volatility months. Uncertainty quantification is essential for energy forecasting applications [57].

The study's findings may provide insights for decision-makers responsible for electricity budgeting at the university. The performance of the proposed Hybrid SES-LSTM Model suggests its potential as a reliable tool for accurate electricity expenditure forecasting. For future work, it would be beneficial to explore the generalizability of the proposed model across various settings and assess its robustness with varying factors influencing electricity expenditure. Furthermore, examining how interpretable the hybrid model's predictions are may help us understand the underlying trends in electricity expenditure data.

4. CONCLUSION

The following conclusions were derived:

1. This study addressed the challenge of forecasting electricity expenditure in universities by developing and evaluating the Hybrid SES-LSTM Model. This study showed the advantage of integrating the interpretability of SES with LSTM's learning capacity to capture both short-term fluctuations and long-term expenditure patterns.
2. This study has a direct contribution to the energy management and financial planning of the university through the proposed model tailored for electricity expenditure. This further strengthens academic institutions' capacity to anticipate costs, optimize resource allocation, and pursue more sustainable operational strategies.
3. Reliable forecasting equips university administrators and policymakers with evidence-based insights for budgeting, risk mitigation, and the implementation of proactive energy management measures, especially in contexts of financial constraints and volatile energy markets.
4. To further advance energy forecasting in academic institutions, future studies should expand the dataset, extend the application of the Hybrid SES-LSTM model to other contexts, and examine external drivers of expenditure patterns. These steps will enhance the model's generalizability, robustness, and interpretability, ensuring its continued relevance as a decision-support tool.

Author Contributions

Jasten Keneth D. Treceñe: Conceptualization, Methodology, Writing-Original Draft, Software, Formal Analysis, Validation. Reynalyn O. Barbosa: Resources, Writing-Review and Editing, Validation. All authors discussed the results and contributed to the final manuscript.

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Declarations

The author declares that there are no conflicts of interest to report in this study.

Declaration of Generative AI and AI-assisted technologies

Generative AI tools (e.g., ChatGPT) were used solely for language refinement (grammar, spelling, and clarity). The scientific content, analysis, interpretation, and conclusions were developed entirely by the authors. The authors reviewed and approved all final text.

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