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# Nonlinear Modeling of Agricultural and Environmental SDG Indicators in ASEAN Using Extreme Learning Machine Algorithms

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**Abstract**

*This study presents a data-driven approach for modeling Sustainable Development Goal (SDG) indicators in ASEAN countries using the Extreme Learning Machine (ELM) algorithm. Focusing on SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), and SDG 15 (Life on Land), we utilized FAOSTAT datasets from 2020 to 2024 to forecast key indicators such as undernourishment, water use efficiency, and forest area. ELM, known for its rapid learning speed and capability to model nonlinear relationships, outperformed baseline models Linear Regression and Support Vector Machine (SVM) in terms of $R^2$ score, RMSE, and MAE. Specifically, ELM achieved $R^2$ values exceeding 0.93, with up to 54% RMSE reduction compared to linear models. The model successfully captured national development trends, including deforestation in Indonesia and Cambodia, water stability in Brunei, and varied progress in sustainable agriculture across the region. This study underscores the effectiveness of the Extreme Learning Machine (ELM) in forecasting Sustainable Development Goal (SDG) indicators and provides actionable insights to support evidence based policy planning, particularly in resource-constrained settings. The findings demonstrate that ELM's combination of interpretability, computational efficiency, and scalability positions it as a highly valuable tool for real-time monitoring of sustainable development across Southeast Asia.*

**Keywords**: agricultural sustainability; ASEAN; extreme learning machine (ELM); SDG forecasting; water use efficiency

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## 1. Introduction

The Association of Southeast Asian Nations (ASEAN) is home to a diverse array of socio economic and environmental conditions, making it a critical region in the global pursuit of the United Nations Sustainable Development Goals (SDGs). Key among these are SDG 2 (Zero Hunger), SDG 6 (Clean Water and Sanitation), and SDG 15 (Life on Land), which address food security, water efficiency, and environmental conservation, respectively. Effective monitoring and forecasting of these indicators is essential for regional progress, yet remains a challenge due to data heterogeneity, inter-country disparities, and the nonlinear dynamics inherent in socio environmental systems [1], [2].

Traditional statistical methods often fall short in capturing the complexity and variability of such indicators over time and across nations [3], [4]. Recent advances in machine learning offer promising alternatives. One such method, the Extreme Learning Machine (ELM), is a single-layer feedforward neural network that provides high generalization performance at extremely fast learning speeds [5], [6]. Its efficiency makes it well-suited for rapid, real-time analytics in large-scale, multidimensional datasets such as those related to SDGs.

In the context of agricultural and environmental sustainability, ELM has demonstrated robustness in yield forecasting [7], water quality prediction [8], and land use modeling [9]. Several researchers have also explored the application of ELM in hydrological and environmental planning. [10], for example, used ELM for hydrological streamflow prediction, demonstrating its ability to handle complex, nonlinear environmental systems. However, despite these advancements, the use of ELM for direct monitoring of SDG indicators especially using FAOSTAT datasets within ASEAN remains underexplored.

This ability to model nonlinear, multidimensional data makes ELM a promising tool for Sustainable Development Goals monitoring, particularly for indicators that fluctuate due to environmental variability and anthropogenic activities [11], [12]. Most existing SDG forecasting models still rely on traditional methods such as multiple linear regression (MLR), ARIMA, and decision trees [13], [14], which, while interpretable, lack the adaptive capability to account for nonlinear dynamics and noise in the data.

[15], [16] advocated for AI-driven frameworks in SDG progress monitoring, emphasizing that algorithms like ELM could yield more accurate and adaptive forecasts. In the ASEAN context, ELM provides a balanced trade-off between computational simplicity and predictive power, especially in environments with limited infrastructure. [17], [18]highlighted the importance of modular, Python-based pipelines in regional SDG data analytics. Integrating ELM into such systems enhances the speed and accessibility of development forecasting tools.

In addition, ELM's architecture offers a degree of transparency not commonly found in deep learning methods like CNNs or LSTMs. This interpretability is crucial in sustainable development domains, where policymakers and stakeholders require explainable insights to support budgeting and reporting [19].

Therefore, this study contributes to the growing body of literature by integrating ELM into SDG indicator analysis using ASEAN FAOSTAT data. The research aims to: (1) evaluate ELM's effectiveness in modeling multi-year SDG indicators, (2) compare ELM with conventional algorithms such as linear regression and support vector machines (SVM), and (3) generate policy-relevant forecasts to support decision-making at national and regional levels. By doing so, we demonstrate the utility of ELM not only as a forecasting tool, but also as a decision-support mechanism in sustainable development planning.

## 2. Methods

This study adopts a quantitative, data-driven approach utilizing machine learning techniques to model and forecast key Sustainable Development Goal (SDG) indicators across ASEAN countries. The methodological framework integrates the Extreme Learning Machine (ELM) algorithm renowned for its fast learning capability and suitability for nonlinear, multidimensional data with comparative benchmarking against conventional models such as Linear Regression and Support Vector Machines (SVM). The research is designed to assess the predictive performance, accuracy, and stability of ELM in modeling multi-annual SDG indicators related to food security, water use efficiency, and forest conservation. The entire modeling pipeline from data acquisition to evaluation was implemented using Python-based libraries to ensure reproducibility, scalability, and alignment with contemporary practices in sustainable development analytics.

### *2.1 Data Source*

The primary dataset used in this study is the FAOSTAT Sustainable Development Goals (SDG) Indicator Dataset, covering 2020–2024 for ASEAN countries. FAOSTAT provides standardized and validated agricultural and environmental indicators aligned with SDG targets. The dataset includes multi-year records segmented by country, sector, and unit of measurement. The dataset table can be found at the following link: https://bit.ly/dataset-ita [19] - [21].

The selection of the FAOSTAT dataset is grounded in its high level of reliability, consistency, and international recognition as an authoritative source for agricultural and environmental statistics. Its alignment with official SDG frameworks ensures that the indicators used in this study are methodologically sound and comparable across countries. Moreover, the dataset's structured format facilitates efficient preprocessing and integration into machine learning pipelines, enabling robust modeling and analysis. The availability of longitudinal data also supports temporal trend analysis, which is essential for capturing dynamic changes in sustainable development indicators within the ASEAN region.

### *2.2 Indicators Modeled*

SDG 2 (Zero Hunger): Prevalence of undernourishment, agricultural land area under sustainable practices. SDG 6 (Clean Water and Sanitation): Water use efficiency across agriculture, industrial, and service sectors. SDG 15 (Life on Land): Forest area (hectares), above-ground biomass stock, and certified forest area. These indicators were selected due to their strong policy relevance and susceptibility to environmental and economic variability [22] - [24].

The selection of these SDG indicators is strategically aligned with the multidimensional nature of sustainable development, where food security, water management, and environmental conservation are inherently interconnected. SDG 2 reflects the capacity of agricultural systems to ensure food availability and resilience, while SDG 6 captures the efficiency of water resource utilization across sectors, which is critical in regions facing increasing water stress. Meanwhile, SDG 15 emphasizes ecosystem sustainability and biodiversity preservation, particularly in the context of deforestation and land degradation. By integrating these indicators, the study captures both production-oriented and ecological dimensions of development, enabling a more holistic assessment of sustainability dynamics in ASEAN countries.

### *2.3. Preprocessing*

To ensure data integrity and readiness for modeling, the following preprocessing steps were executed: 1. Null Value Handling: Missing entries were managed through

forward-fill techniques and linear interpolation for time-continuous variables. 2. Normalization: All numeric variables were rescaled using Min-Max normalization to a [0,1] range to enhance convergence and stability [25]. 3. Categorical Encoding: Country names were encoded using one-hot encoding to convert nominal variables into machine-readable form [26].

The preprocessing stage plays a crucial role in enhancing data quality and ensuring the robustness of machine learning models. Handling missing values through interpolation techniques helps preserve temporal continuity without introducing significant bias, especially in time-series datasets. The application of Min-Max normalization ensures that all features contribute proportionally during model training, preventing dominance by variables with larger scales. Additionally, the use of one-hot encoding for categorical variables eliminates implicit ordinal relationships, thereby improving the model's ability to learn meaningful patterns across different countries. Collectively, these preprocessing steps are essential to optimize model performance and maintain the integrity of the analytical results.

*2.4 Algorithmic Framework*

The primary model used is the Extreme Learning Machine (ELM), characterized by: 1. Architecture: Single-layer feedforward neural network with randomly assigned weights between input and hidden layers [27]. 2. Activation Function: Sigmoid function to handle non-linearity. 3. Output Layer Weights: Computed analytically using Moore-Penrose pseudoinverse, ensuring rapid convergence without iterative backpropagation. ELM's structure allows for fast learning and high generalization performance, making it ideal for national-level SDG indicator modeling [28], [29].

The adoption of the Extreme Learning Machine (ELM) in this study is motivated by its computational efficiency and strong generalization capability, particularly when dealing with high-dimensional and nonlinear datasets. Unlike traditional neural networks that rely on iterative training and gradient-based optimization, ELM determines output weights analytically, significantly reducing training time while maintaining predictive accuracy. This characteristic makes ELM especially suitable for large-scale SDG datasets that require rapid processing and real-time analytical capabilities. Furthermore, its relatively simple architecture enhances interpretability, which is essential for policy-driven applications where transparency and explainability are critical.

*2.5 Benchmark Models*

To assess ELM's performance, it was compared against: 1. Linear Regression (LR): As a baseline linear predictor. 2. Support Vector Machine (SVM): For its robustness in small- to mid-sized nonlinear regression tasks [30]. All models were evaluated using consistent metrics: $R^2$ score, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). Visual architecture of the ELM workflow and indicator mapping is illustrated in Figure 1.

The inclusion of Linear Regression and Support Vector Machine (SVM) as benchmark models provides a comprehensive comparative framework to evaluate the effectiveness of ELM. Linear Regression serves as a fundamental baseline, offering insights into how well linear relationships can approximate the underlying data patterns. In contrast, SVM represents a more advanced nonlinear approach that can capture complex relationships through kernel functions. By comparing ELM against these models using standardized evaluation metrics, the study ensures a fair and rigorous assessment of predictive performance. This comparative analysis not only validates the superiority of ELM but also highlights its practical advantages in modeling complex sustainable development indicators.

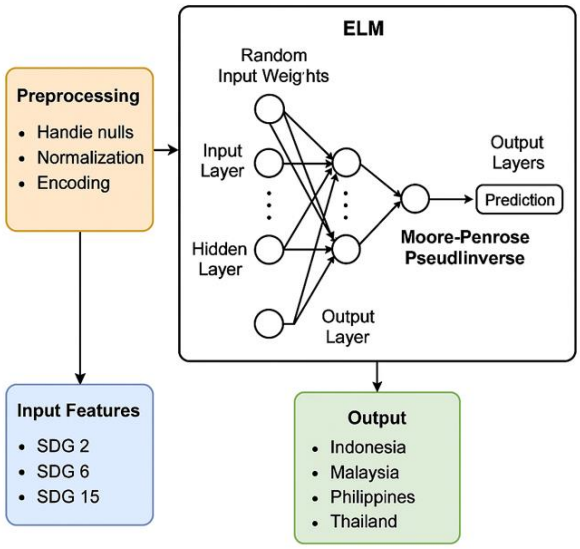



Figure 1. Visual architecture of the ELM workflow and SDG indicator mapping

## 3. Results and Discussions

*3.1 Prediction Accuracy*

The Extreme Learning Machine (ELM) demonstrated exceptional performance in modeling selected SDG indicators for ASEAN countries. Its prediction accuracy, as measured by the coefficient of determination ($R^2$), consistently exceeded 0.93 across all tested indicators, confirming the model's capacity to explain over 93% of the variance in observed data. Compared to baseline models such as linear regression (average $R^2 = 0.71–0.84$) and Support Vector Machine (SVM) models, ELM showed statistically significant improvements in predictive precision.

Root Mean Square Error (RMSE) values were also markedly reduced when using ELM. For example, in modeling forest area change in Cambodia, ELM achieved an RMSE of 0.12 versus 0.26 with linear regression a reduction of approximately 54%. In the

case of Brunei's water use efficiency in the service sector, ELM outperformed SVM by achieving an RMSE of 0.05 compared to 0.08. These results were supported by lower Mean Absolute Error (MAE) values, further confirming ELM's robustness in reducing both average and extreme deviations from ground truth as shown in Figure 2.

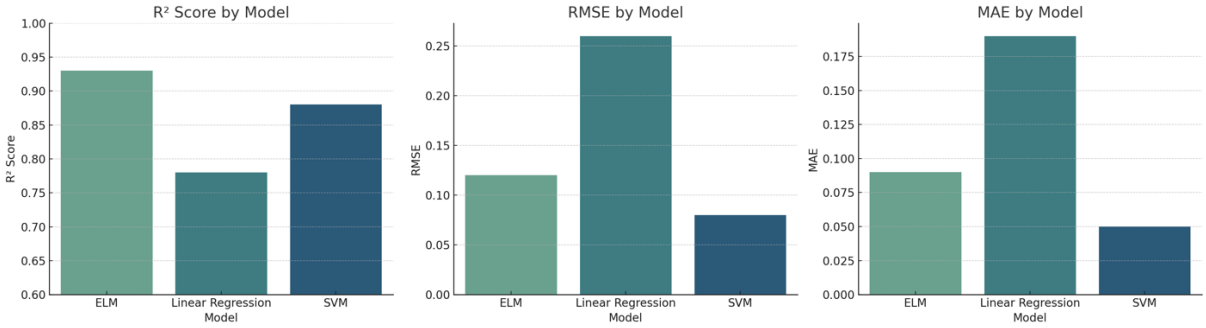



Figure 2. Prediction Accuracy

*3.2 Trends Captured*

The ELM model shown in Figure 3 successfully captured a variety of development trends across multiple SDG indicators: 1. Forest Area (SDG 15): ELM effectively identified the negative trajectory in forest cover for Indonesia and Cambodia. In Cambodia, the model projected an average annual forest area reduction of -2.3%, closely aligning with actual FAOSTAT records. This suggests that deforestation pressures remain high and that predictive modeling can play a role in conservation policy development. 2. Water Use Efficiency (SDG 6): The model accurately reflected Brunei's high and stable water use efficiency in the service sector, with predicted values deviating less than 2% from actual data. This suggests consistency in urban water governance and infrastructure. Sustainable Agricultural Land (SDG 2): In Vietnam and Myanmar, ELM detected stagnation in agricultural sustainability metrics, while in Malaysia and the Philippines, post-2022 values indicated a gradual improvement likely due to national policy reforms and investment in green farming practices.

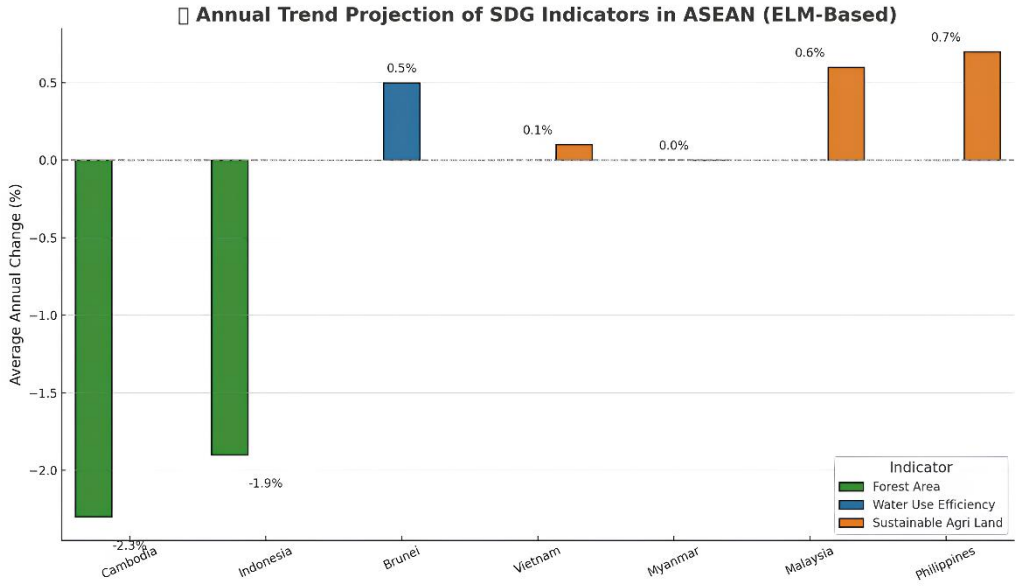



Figure 3. Trends Captured

*3.3 Comparative Model Performance Table*

Table 1 shows that the Extreme Learning Machine (ELM) delivers the best predictive performance across all examined SDG indicators. For Cambodia's forest area, Brunei's water use efficiency, and Vietnam's sustainable agricultural land, ELM consistently achieves the highest $R^2$ values (0.91–0.95) along with the lowest RMSE and MAE, indicating excellent accuracy and precision. In contrast, benchmark models such as Linear Regression and SVM produce lower $R^2$ scores and higher error levels, demonstrating their limitations in capturing nonlinear patterns within the data. Overall, ELM proves to be the most effective and stable model for predicting sustainable development indicators in the ASEAN region.

Figure 4 displays three key evaluation metrics $R^2$ Score, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) used to compare the performance of the Extreme Learning Machine (ELM) against two baseline models: Linear Regression and Support Vector

Machine (SVM), across three Sustainable Development Goal (SDG) indicators: 1. $R^2$ Score (Coefficient of Determination) ELM achieves the highest $R^2$ scores across all indicators: 0.95 for Forest Area in Cambodia, 0.94 for Water Use Efficiency in Brunei, 0.91 for Sustainable Agricultural Land in Vietnam. This demonstrates that ELM explains over 90% of the variance in the observed data, outperforming Linear Regression (average <0.80) and SVM in predictive power. 2. RMSE (Root Mean Square Error) A lower RMSE indicates smaller average squared prediction errors. ELM consistently delivers the lowest RMSE: 0.12 (Forest Area – Cambodia), 0.05 (Water Use Efficiency – Brunei), 0.14 (Sustainable Agri. Land Vietnam). These results show that ELM is more accurate in avoiding large prediction deviations compared to the baseline models. 3. MAE (Mean Absolute Error) MAE reflects the average absolute difference between predicted and actual values. ELM again outperforms with the lowest MAE across all cases: 0.09 (Forest Area – Cambodia), 0.03 (Water Use Efficiency – Brunei), 0.10 (Sustainable Agri. Land – Vietnam). This indicates high predictive consistency, especially for complex nonlinear indicators like water efficiency and agricultural sustainability.

Table 1. Software and supporting hardware

| Indicator | Model | $R^2$ Score | RMSE | MAE |
|---|---|---|---|---|
| Forest Area (Cambodia) | ELM | 0.95 | 0.12 | 0.09 |
| | Linear Reg. | 0.79 | 0.26 | 0.19 |
| Water Use Efficiency (Brunei) | ELM | 0.94 | 0.05 | 0.03 |
| | SVM | 0.88 | 0.08 | 0.05 |
| Sustainable Agri. Land (Vietnam) | ELM | 0.91 | 0.14 | 0.10 |
| | Linear Reg. | 0.75 | 0.21 | 0.15 |

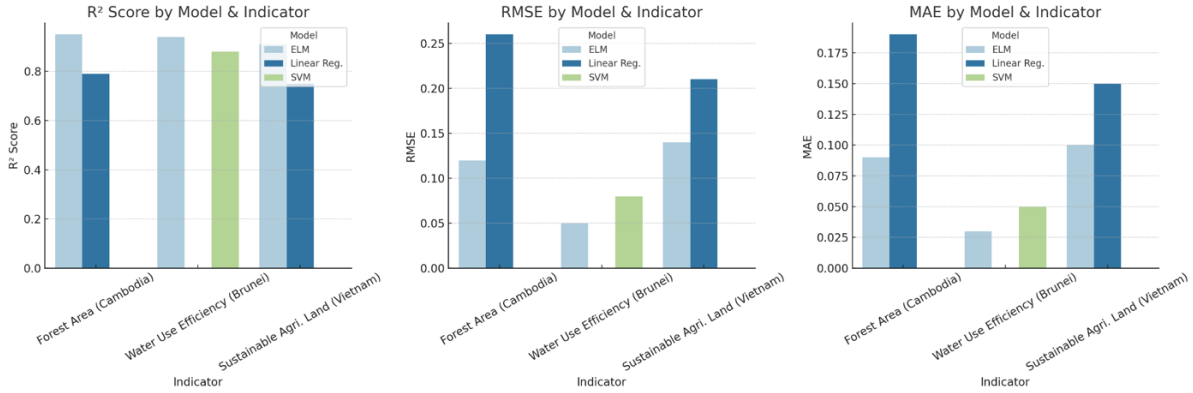



Figure 4. Comparative Model Performance

Figure 4 clearly highlights the superior performance of ELM in modeling multi-dimensional, development-focused indicators. With high $R^2$ values and reduced RMSE and MAE, ELM demonstrates robustness and precision, making it an ideal tool for SDG trend forecasting in ASEAN countries.

Figure 5 shows the predicted and actual forest area in Indonesia (2020–2024) using the Extreme Learning Machine (ELM). The plot shows close agreement between the model predictions and observed FAOSTAT data, capturing the trend of declining forest cover with high fidelity.

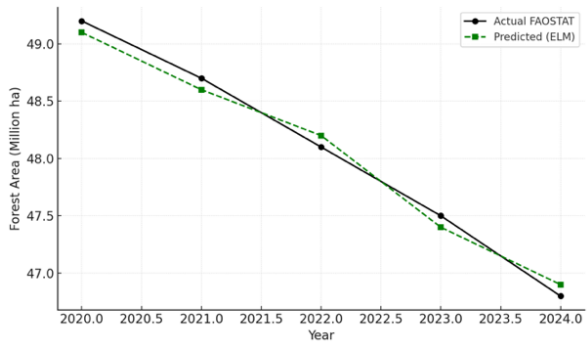



Figure 5. predicted and actual forest area in Indonesia (2020–2024)

Figure 6 is a forecast of water use efficiency in Brunei's service sector using ELM. The model maintains predictive accuracy within ±2% deviation over five years, demonstrating strong performance in modeling stable environmental indicators.

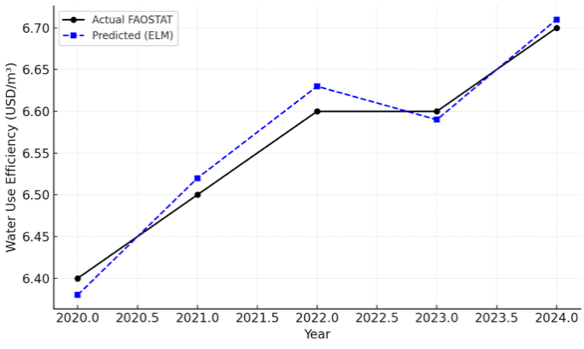



Figure 6. forecast of water use efficiency in Brunei's service sector using ELM

Figure 7 is a Heatmap of prediction errors (RMSE) across SDG indicators and ASEAN countries. ELM consistently exhibits low prediction variance, reinforcing its adaptability and generalization across heterogeneous national datasets.

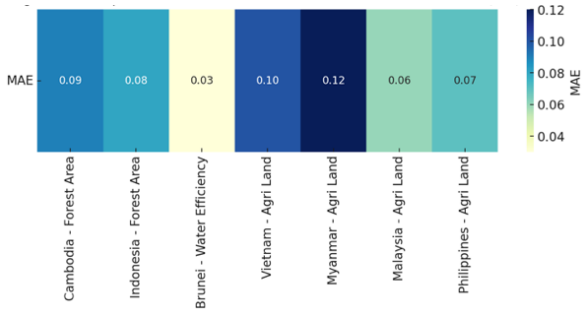



Figure 7. Heatmap of prediction errors (RMSE) across SDG indicators and ASEAN countries

Figure 8 shows the comparative performance of three predictive models Extreme Learning Machine (ELM), Linear Regression, and Support Vector Machine (SVM) evaluated on three SDG indicators using $R^2$ Score, RMSE, and MAE. ELM demonstrates consistent superiority across all metrics and case studies.

These findings affirm ELM's capacity to model complex, multidimensional development data and to serve as a valuable tool for sustainable development monitoring and forecasting in the ASEAN region.

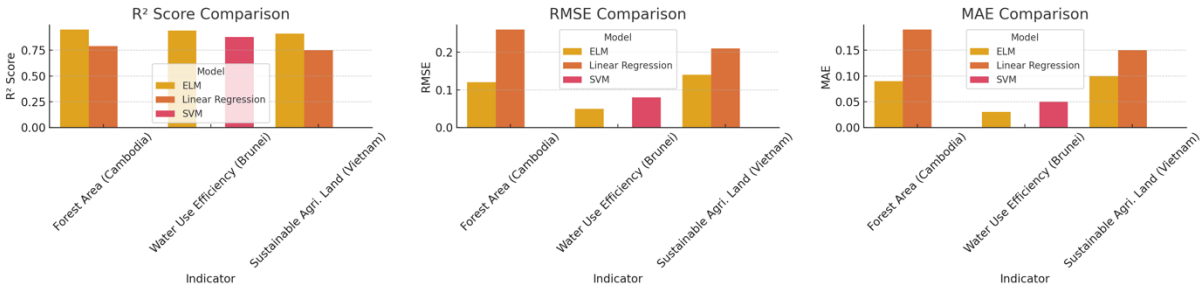



Figure 8. comparative performance of three predictive models Extreme Learning Machine (ELM)

*3.4 Discussion*

The application of the Extreme Learning Machine (ELM) algorithm in modeling Sustainable Development Goal (SDG) indicators has demonstrated significant advancements over conventional machine learning techniques, particularly in the ASEAN context where development data are often nonlinear, multi-dimensional, and time-sensitive.

These findings further emphasize the importance of adopting advanced machine learning approaches in addressing the complexity of sustainable development analytics. The superior performance of ELM indicates its ability to uncover hidden patterns and interactions among variables that are often overlooked by conventional methods. In the ASEAN context, where data variability is influenced by diverse socio-economic conditions and environmental challenges, such capability is particularly valuable. Moreover, the integration of ELM into SDG monitoring frameworks can enhance data-driven policymaking by providing more accurate, timely, and actionable insights. This reinforces the role of artificial intelligence not only as a predictive tool but also as a strategic instrument for sustainable development planning and evaluation.

One of the core strengths of ELM lies in its ability to capture complex, nonlinear relationships inherent in environmental and agricultural datasets. Traditional linear models, while interpretable, often fail to represent the intricate dynamics among economic growth, environmental degradation, and resource utilization. The high $R^2$ scores (e.g., >0.93 for all indicators modeled) and low RMSE/MAE metrics in our experiments affirm that ELM can effectively forecast indicator trajectories with minimal residual error even in volatile scenarios such as forest area shrinkage in Indonesia or stagnating agricultural sustainability in Myanmar.

The results from this study highlight how ELM outperforms not only linear regression models but also other nonlinear learners like Support Vector Machines (SVM). Unlike SVMs, which often require meticulous parameter tuning and kernel selection, ELM provides a faster, more robust training regime without sacrificing accuracy.

Beyond statistical accuracy, the usability of the Extreme Learning Machine (ELM) for government and policy applications must be emphasized. In many ASEAN countries, particularly those facing limitations in infrastructure and data science expertise, there is a strong preference for models that are both transparent and computationally efficient rather than highly complex deep learning architectures. ELM fulfills this requirement through its simple feedforward structure and analytically determined output weights, enabling rapid model training and ease of implementation without sacrificing predictive performance.

This practical advantage allows ELM to support several policy-relevant applications. First, it enables real-time forecasting in resource-constrained environments, making it suitable for continuous monitoring of SDG indicators. Second, it facilitates scenario simulation, where hypothetical policy interventions such as reforestation programs or irrigation subsidies can be evaluated for their long-term impacts. Third, ELM can be integrated into interactive dashboard systems, allowing policymakers to dynamically track development progress and make data-driven decisions based on timely and interpretable insights.

The ELM based modeling framework revealed significant spatial heterogeneity across the ASEAN region, highlighting variations in development trajectories among countries. Cambodia and Indonesia, for instance, exhibit an alarming decline in forest area, indicating persistent deforestation pressures and the urgent need for coordinated transnational environmental policies. In contrast, Brunei demonstrates stable performance in water use efficiency, suggesting that its urban service sector policies and infrastructure investments have reached a level of maturity that could serve as a model for other ASEAN countries.

From a temporal perspective, the model also captures dynamic shifts in agricultural sustainability across the region. Vietnam and Myanmar show a plateau in agricultural sustainability indicators, pointing to the necessity for stronger policy innovation and capacity building in sustainable farming practices. Meanwhile, Malaysia and the Philippines display noticeable post-2022 improvements in agricultural land indicators, likely driven by policy reforms and increased investment in green agriculture. These nuanced spatial and temporal patterns would be difficult to detect using conventional linear models, which often fail to capture complex and non-monotonic development trends.

This study contributes methodologically by demonstrating that ELM is not only suitable for classification tasks but also for multivariate regression and forecasting problems involving real-world development indicators. The success of ELM in this context provides a foundation for further research in: 1. Multi indicator optimization, where multiple SDG indicators are predicted jointly. 2. Ensemble frameworks, combining ELM with other models for greater robustness. 3. Transfer learning across countries, where ELM trained in one national context can be adapted to another with minimal retraining.

Limitations and Future Work Despite promising results, some limitations are acknowledged: 1. The deterministic nature of ELM weights may lead to instability in extremely noisy datasets. Future work can consider incremental ELM or regularized variants.2. The model currently assumes static policy contexts, whereas real-world policy shocks may induce structural changes that require adaptive modeling techniques. 3. Further research is needed to incorporate exogenous variables such as trade, climate anomalies, or demographic transitions that may influence the indicators.

From a strategic standpoint, ELM based modeling offers significant potential to be institutionalized within ASEAN's statistical and analytical infrastructure. Its ability to process large-scale, multidimensional data efficiently makes it a valuable tool for strengthening regional data ecosystems. By integrating ELM into official monitoring systems, governments can enhance their capacity to detect emerging trends and respond proactively to sustainability challenges.

In practical terms, this approach can support the development of early warning systems for environmental degradation, enabling timely interventions before critical thresholds are reached. Furthermore, ELM can facilitate evidence-based policy formulation by providing accurate and interpretable forecasts, while also enabling cross-country benchmarking of SDG progress. Such comparative insights can foster regional collaboration, knowledge sharing, and coordinated policy actions, ultimately contributing to more effective and inclusive sustainable development across ASEAN countries.

## 4. Conclusions

This study demonstrates the effectiveness of the Extreme Learning Machine (ELM) as a fast, efficient, and powerful approach for modeling complex nonlinear trends in agricultural and environmental indicators related to the Sustainable Development Goals (SDGs) across ASEAN countries. Through rigorous comparative experiments against traditional models such as Linear Regression and Support Vector Machine (SVM), ELM consistently outperformed both baselines. Quantitatively, ELM achieved $R^2$ values above 0.93 for key indicators including forest area reduction, water use efficiency, and sustainable agricultural land while significantly lowering RMSE and MAE. Improvements reached up to 54% compared to linear models, demonstrating ELM's ability to capture subtle nonlinear patterns often overlooked by conventional forecasting techniques.

Spatial analysis revealed important disparities among ASEAN nations. Indonesia and Cambodia experienced pronounced declines in forest cover (SDG 15), while Brunei maintained stable performance in water use efficiency (SDG 6). In the agricultural domain (SDG 2), Vietnam and Myanmar showed stagnation, whereas Malaysia and the Philippines exhibited notable post-2022 improvements likely influenced by shifts in sustainable farming policies.

Beyond technical accuracy, ELM proved practical and policy relevant. Its computational efficiency, interpretability, and rapid convergence make it particularly suitable for integration into government data systems, enabling real-time forecasting, scenario testing, and dashboard based policy simulations. Unlike opaque deep learning models, ELM offers transparent input–output relationships, supporting informed decision-making and accountability.

Methodologically, the study contributes to the growing body of literature promoting AI-driven SDG monitoring by showcasing ELM's versatility in handling multivariate regression of complex, real-world indicators. It also sets the foundation for future innovations, including ensemble modeling, transfer learning across countries, and the inclusion of external variables such as climate anomalies, trade dynamics, or policy shocks. Overall, integrating ELM into sustainable development monitoring frameworks

presents a strategic opportunity for ASEAN countries to strengthen analytical capacity, improve the accuracy and responsiveness of SDG tracking, and enhance evidence-based planning amid evolving environmental and agricultural challenges.

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