ENCUENTROS | Revista de Ciencias Humanas, Teoría Social y Pensamiento Crítico pp: 417-436

EVOLUTION OF THE SME LOAN PORTFOLIO IN ECUADOR: A HOLT- WINTERS APPROACH AND THE EXTREME LEARNING MACHINE NETWORK

Evolución de la cartera de crédito de las PYMES en Ecuador: un enfoque Holt-Winters y la red Extreme Learning Machine

Armando José Urdaneta Montiel
Universidad Metropolitana del Ecuador. Machala, Ecuador.
aurdaneta@umet.edu.ec
https://orcid.org/0000-0002-9825-9453

Leopoldo Wenceslao Condori Cari
Universidad Andina Néstor Cáceres Velásquez. Juliaca, Perú.
leowen0621@hotmail.com
https://orcid.org/0000-0003-2372-6720

Ángel Alberto Zambrano Morales
Universidad Metropolitana del Ecuador. Machala, Ecuador.
azambrano@umet.edu.ec
https://orcid.org/0000-0002-7897-7327

José Roberto Morales Vergara
Universidad de Guayaquil, Guayaquil, Ecuador.
Roberto.moralesv@ug.edu.ec
https://orcid.org/0000-0001-7814-3624

Este trabajo está depositado en Zenodo:
DOI: https://doi.org/10.5281/zenodo.15467671

ABSTRACT

This mixed-method research focused on predicting the evolution of the portfolio of credits to SMEs in Ecuador. The Holt-Winters model and the Extreme Learning Machine network, combining econometric models and neural networks, were employed, along with geospatial analysis at the provincial level. The model exhibited optimal fitting to real data, effectively capturing 93% of their variability, and demonstrated efficient forecasting with slightly superior performance compared to other analyzed models. This outcome holds crucial importance for decision-making and financial resource planning dedicated to Ecuadorian SMEs.

Keywords: Credit portfolio, SMEs, Holt-Winters, credit planning, efficiency, neural networks.

RESUMEN

Esta investigación, de enfoque mixto, se basó en la predicción de la evolución de la cartera de créditos a PYMES en Ecuador. Se utilizó el modelo Holt-Winters y la red Extreme Learning Machine, que combinan modelos econométricos y redes neuronales, acompañados del análisis geoespacial a nivel de provincias. El modelo presentó ajuste óptimo de los datos reales, comprende eficazmente el 93 % de la variabilidad de estos, muestra un eficiente pronóstico y rendimiento ligeramente superior sobre otros modelos analizados. Este resultado es crucial para la toma de decisiones y la planificación de los recursos financieros destinados a las PYMES ecuatorianas.

Palabras claves: Cartera de créditos, PYMES, Holt-Winters, planificación crediticia, eficiencia, redes neuronales.

RECIBIDO: 17/11/2024 ACEPTADO: 17/02/2025

INTRODUCTION

The main objective of this study was to forecast the future evolution of the SME loan portfolio in Ecuador. For this purpose, the Holt-Winter model was applied through a dynamic software tool that facilitates credit planning for the country's banking sector. The Holt-Winters model was developed by Charles Holt and Peter Winter in 1960 ((Winters, 1960)) and cited by Pleños (2022), who points out that the triple exponential smoothing model is used to predict future values of time series that exhibit trend and seasonality patterns; it has three components of level, trend and seasonality, and has been used successfully in various areas, from energy planning to retail sales forecasting and economic analysis. The relevance of accurate forecasting in these areas is undeniable, as it facilitates strategic decision making, resource planning and market optimization

In the field of residential electricity consumption forecasting, Mejía and Gonzáles (2019) use it as a key tool for energy planning at regional and national levels, with the objective of making a forecast that allows balancing supply and demand, managing production and distribution, guaranteeing a reliable supply, and enabling electricity market agents to make strategic decisions, such as adjusting supply, planning new facilities, and setting appropriate prices.

Liu *et al.* (2020) also use the Holt-Winter model for residential electricity consumption prediction, but under a hybrid Extreme Learning Machine network model, in order to verify its adaptability to changes in data characteristics. The authors conclude that this hybrid model is effective in predicting residential electricity consumption and outperforms other models in terms of performance. They highlight its stability and adaptability to different data sets and training set sizes.

The importance of accurate forecasting of residential electricity consumption lies in its usefulness for energy management according to Almazrouee *et al.* (2020), who using the Prophet and Holt-Winters models are able to accurately predict the long-term electricity load in Kuwait, facilitating energy system planning, demand response strategies and maintenance of energy equipment, as well as optimization of electricity markets.

Regarding economic series Lima *et al.* (2019) propose in their research to compare the accuracy of Holt-Winters exponential smoothing models (additive and multiplicative); they focused on evaluating these models in the prediction of e-commerce retail sales in Portugal, concluding that the multiplicative model showed better performance in terms of prediction accuracy.

In the same vein Dritsaki and Dritsaki (2021), comparing the performance of two popular forecasting techniques (ARIMA models and the Holt-Winters exponential smoothing method) to determine which provides more accurate predictions of GDP per capita in five Balkan countries, after the COVID-19 pandemic, they conclude that both methods can provide accurate predictions in the countries examined, that the COVID-19 pandemic had a significant impact on the economy of those regions, and that economic recovery is expected to be gradual and slow.

The literature review focused on the analysis of economic theory and the application of multiple empirical works to understand the evolution of the SME loan portfolio in the province of El Oro, Ecuador. It was then contextualized with relevant statistics on bank credit and macroeconomic aggregates in the country. Finally, forecasts of the variables were made, and a geospatial synthesis was added to the analysis by means of heat maps of Ecuador. This study is part of the research project "Mechanism of promotion and access to financing developed by the Ecuadorian banking system for the financing of SMEs in the province of El Oro", contributing to the knowledge and understanding of the financial dynamics in this specific context.

LITERATURE REVIEW

With regard to forecasting the evolution of the SME loan portfolio in Ecuador, a study that makes a valuable contribution due to the econometric models used is that of Sulaiman and Juarna (2021), who make a forecast of unemployment in Indonesia using two-time series models, ARIMA and Holt-Winters, based on data collected between 2005 and 2019. After comparing the two models, Holt-Winters was found to be the most accurate in predicting unemployment in the next two years, with lower mean square error and root mean square error compared to ARIMA. The paper also examines the causes of unemployment in Indonesia, such as urbanization, industrialization, the share of workers with a high school degree, and the provincial minimum wage.

On the other hand, the research presented by Ahmar *et al.* (2021) focuses on the prediction of stock prices in the BRIC countries (Brazil, Russia, India and China) during the context of the COVID-19 pandemic, using three forecasting models: ARIMA, SutteARIMA and Holt-Winters. The findings indicate that the Holt-Winters model proves to be the most appropriate for anticipating stock price movements in Brazil, while the SutteARIMA model proves to be more appropriate for predicting stock prices in Russia, India and China. This study underlines the relevance of accurate stock price forecasts in periods of economic crisis and highlights how this information can be crucial for policymakers' decision-making.

Research by Karadžić and Pejović (2021) compares the accuracy of three types of inflation forecasting models: Holt-Winters, ARIMA and NNAR models, for countries in the European Union and the Western Balkans. They are compared according to seven accuracy criteria. It is concluded that NNAR forecasts more accurately for the Western Balkan countries, while ARIMA forecasts 12-month inflation more accurately for the EU countries. Holt-Winters models rank second for both groups of countries. The paper provides a review of the literature on inflation forecasting and presents a detailed methodology for each of the three models evaluated.

In the same vein, Atoyebi *et al.* (2023) focus on forecasting the quantity of currency in circulation (CIC) in the Nigerian economy through the Holt-Winters exponential smoothing method, covering an extended period of data from January 1960 to December 2022. The results highlight that the multiplicative Holt-Winters approach outperforms the additive approach in terms of accuracy in CIC predictions. It highlights the importance of CIC in the Nigerian economy, where an increase in its share restricts credit, limits economic growth, can contribute to inflationary pressures and signal a short-term economic boom. This research provides valuable insights into the relationship between the CIC and crucial macroeconomic variables, benefiting the field of economics and monetary management in Nigeria.

The Holt-Winters model is appropriate for analysing data sets that exhibit trend and seasonality patterns, as also noted by Hidayat and Darmawan (2023). This method is used in the decomposition process to discern the components related to both patterns in the time series data. However, in a comparative study on stock price prediction, in particular using PT Telkom Indonesia's TLKM stock, the SARIMA model and the Holt-Winters Seasonal Smoothing model were evaluated. The research included an analysis of the models' accuracy using error metrics such as MAPE, MAE and RMSE, and the results indicated that the SARIMA model outperforms the Holt-Winters model in terms of the accuracy of stock price predictions.

The Holt-Winters model is a quantitative forecasting technique that can be used as a tool for long-term strategic planning in a company (Apichatibutarapong, 2015). Moreover, it can help the firm to make more rational decisions and minimize uncertainty by estimating various future aspects of the business, such as production scheduling, future sales, raw material purchasing and inventory policies. However, Naim *et al.* (2018) point out that this model is not suitable for handling complex seasonal patterns in time series, and indicate that traditional time series methods such as ARIMA, SARIMA and ETS are designed to handle single seasonality patterns in a series, but with the presence of multiple seasonalities these methods do not work satisfactorily. Therefore, it is required to use advanced techniques such as BATS (Box-Cox Transformations, ARMA errors, Trend, Seasonal components) and TBATS (Trigonometric seasonality, Box-Cox transformation, ARMA errors, Trend, Seasonal components), which have proven to be more effective in predicting multiple seasonality patterns in time series.

Finally, in order to improve accuracy and advance forecasting theory and practice, Makridakis *et al.* (2020) employed 100,000 time series that included forecast intervals in the evaluation. The results of this competition are thoroughly detailed, highlighting the most effective methods and their main findings, as well as their implications for forecasting theory and practice and possible directions for future research. The study examines the organization and process of the competition, as well as the computational requirements of the various forecasting methods. Relevant references of great interest in the subject are provided.

Among the techniques evaluated in the competition, the Holt model and the Holt-Damped model are mentioned, both based on exponential smoothing, which consider linear trends and damping components. It should be noted that the Holt-Winter model, widely used in time series forecasting, was part of the M4 Competition. The results of the competition indicated that the performance of the Holt-Winter model was inferior compared to other forecasting methods in several application scenarios, especially in the prediction of complex seasonality patterns in time series, where it was outperformed by Artificial Intelligence based models.

The literature review provides a valuable context for the main objective of the study, which is to forecast the future evolution of the SME loan portfolio in Ecuador. The reviewed literature addresses the use of ARIMA, Holt-Winters and other models in different contexts, such as unemployment forecasting in Indonesia and the prediction of stock prices in BRIC countries during the COVID-19 pandemic. These studies demonstrate the relevance of having this type of accurate models in times of economic uncertainty and highlight the importance of choosing the right ones for each situation.

It is also mentioned that, although the Holt-Winters model is widely used, it can be outperformed by more advanced models, such as BATS and TBATS, for predicting complex seasonality patterns in time series. It is important to consider these advanced techniques applied to the SME credit portfolio in Ecuador, especially in a context of multiple seasonalities and complexity in time series data. The M4 competition is highlighted as an important effort in the field of forecasting, which evaluated various methods and provided valuable information on their performance. Overall, this review provides a solid contextual framework for the present study.

On the other hand, in the field of time series forecasting, there has been a growing interest in the application of Extreme Learning Machine (ELM) as an effective tool to address forecasting problems. According to Li et al. (2019), ELM stands out as a linear kernel function that can implicitly map the input time series into a feature space. This gives it continuous, non-negative and symmetric properties, which strengthen its generalizability and stabilize the output weights. In their study on multi-step bin forecasting, they used both the kernel function ELM and the kernel ELM (KELM) to achieve accurate primary and secondary decomposition results (Li et al., 2019).

In the same vein Wang et al. (2018) highlight that ELM is a simple and efficient learning algorithm that has been shown to be effective in nonlinear time series forecasting. Its feature of not requiring parameter tuning and its ability to overcome problems such as local minima and time consumption make ELM an attractive tool for time series forecasting.

In another context Deina et al. (2021) describe the ELM as a direct feed-forward neural network architecture with a single intermediate layer. What is distinctive about the tool is that the weights of this layer are randomly generated and kept unadjusted, which simplifies the training process. These authors emphasize that the ELM is capable of approximating any continuous, non-linear, differentiable and bounded function, which makes it suitable for solving challenging forecasting problems.

At the same time, Sokolov-Mladenović et al. (2016) also highlight the advantages of ELM compared to conventional learning algorithms, such as backpropagation (BP). ELM is used in single hidden-layer artificial neural networks (ANNs), which results in fast training and good generalization. According to these authors, ELM addresses problems caused by gradient descent-based algorithms, such as backpropagation, and significantly reduces the time needed for ANN training.

Finally, Pang et al. (2021) use ELM to build a borrower credit score model and assess borrower default risk. They highlight that ELM is a fast and accurate machine learning model that can overcome convergence and generalization problems in other machine learning models. Taken together, these studies support the effectiveness of ELM in a variety of applications, including time series forecasting and credit scoring model building.

METHOD

The work had a mixed research approach combining qualitative and quantitative elements (Bairagi and Munot, 2019) to comprehensively study the evolution of the credit portfolio destined to SMEs in Ecuador. The research is structured in three phases:

Phase 1: Comparative geospatial analysis (qualitative and quantitative).

Geospatial analysis involves the process of collecting, visualizing, modifying, and understanding geographic information in order to identify patterns, trends, and insights useful for decision making (Longley et al., 2015). This approach combines Geographic Information Systems (GIS) technology with statistical tools and spatial analysis to examine relationships between diverse data sets linked to specific geographic locations. It is used in a wide range of applications, including the study of climate and environment, urban planning, and market research (Diaz *et al*., 2014). In terms of accuracy, ease of use, and the increasing diversity of devices with geospatial capabilities, this discipline has advanced significantly.

In this stage, the collection of relevant regional geostrategic and economic data (Coaquira et al., 2023), for the years 2012 and 2022 by province, including crucial variables such as total credit portfolio, SME credit portfolio and its growth rate, and the share of the SME credit portfolio in the total credit portfolio, is carried out. Through descriptive analysis, general trends and spatial patterns in the evolution of these variables over time were identified using geospatial visualization tools that effectively represent the data. In addition, a temporal comparison of these variables at the provincial level was made, allowing the evaluation of differences and similarities in their evolution for different geographic regions.

Phase 2: SME loan portfolio forecasting (quantitative)

In this phase, an innovative hybrid forecasting model was implemented, combining the Holt-Winters method and the Extreme Learning Machine (ELM) network according to Liu *et al*. (2020), to predict the amounts granted in the SME loan portfolio, considering the period from January/2010 to December/2028. The model was adjusted and calibrated using historical data for this item. To verify the adaptability of the model to changes in data characteristics, according to Zhou *et al.* (2022), a cross-validation was carried out and its performance is evaluated using appropriate error metrics such as MAE (Mean Absolute Error), MSE (Mean Squared Error) and RMSE (Root Mean Squared Error).

The hybrid model allows taking advantage of the strengths of both approaches to provide accurate predictions. While Holt-Winters is ideally suited to address time-related patterns, ELM stands out for its ability to capture more intricate relationships that might not be evident from historical data alone (Liu et al., 2020). The combination of these two techniques promises a completer and more accurate picture of the dynamics of SME credit portfolios in the Ecuadorian economic context.

Phase 3: Analysis and interpretation of results (qualitative and quantitative)

In this stage, an interpretation of the results generated by the hybrid forecasting model is made. It analyzes how geospatial and economic variables influence the evolution of the SME loan portfolio and discusses the findings extensively, considering both qualitative and quantitative aspects; it also examines their significance in the economic and geospatial context. The key conclusions of the study are summarized and recommendations are provided to support financial and economic decision making. Finally, the entire research process is documented, ensuring transparency and replicability of the methodology and results.

This mixed research approach is presented as a sound methodology to address the analysis and forecasting of the SME credit portfolio in Ecuador, allowing for a comprehensive understanding of its evolution in the economic and geospatial context of the country.

RESULTS

The results of the comparative geospatial analysis (qualitative and quantitative), corresponding to the variable Percentage of participation of the province in the SME credit portfolio at the national level, were based on the following hypothesis system:

Null hypothesis (H_0): There is no significant difference in the percentage share of the province in the SME credit portfolio at the national level between the two groups.

Alternative hypothesis (H_1): There are significant differences in the province's percentage share of the SME loan portfolio at the national level between the two groups.

Table 1 provides t-test results for independent samples in two different situations (one assumes equal variances and the other does not) and analyzes each of the tests separately for Ecuador, in the years 2012 and 2022. The Levene's test for quality of variances shows that the p-value is 0.818, indicating that there is no significant evidence to reject equality of variances (equal variances are assumed). In the t-test for equality of means, the p value is 1.000; this shows that there is no relevant certainty to reject the null hypothesis. Therefore, it is concluded that there is no appreciable difference in the province's percentage share of the SME loan portfolio at the national level between the two groups (2012 and 2022).

Table 1.

Levene's test for quality of variances and t-test for equality of means for the variable "Percentage share of the province in the SME loan portfolio at the national level".

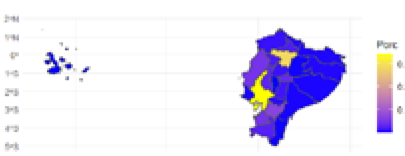
Percentage of the province's share of the SME loan portfolio at the national level									
	Levene's test		t-test for equality of means						
	F	Sig.	t	df	Sig. (bilateral)	Difference in averages	Standard error difference	95 % confidence interval of the difference	
								Lower	Upper
Equal variances are assumed	.054	.818	.000	46	1,000	-.0000042	.0267191	-.0537870	.0537787
Equal variances are not assumed			.000	45,207	1,000	-.0000042	.0267191	-.0538125	.0538041

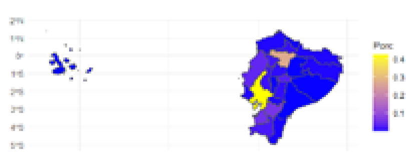
Source: Superintendency of Banks (2022).

The 2012 and 2022 heat maps indicate that the SME loan portfolio at the national level, in the last 10 years, continues to be concentrated in the provinces identified with the yellow color: Guayas and Pichincha between 63% and 70%; then follow the provinces of Azuay, Manabí and El Oro, which account for 16% of this portfolio (See Figure 1).

Figure 1.

Heat maps of Ecuador for the variable "Percentage of participation of the province in the SME loan portfolio at the national level".





Heat map year 2012
Heat map year 2022

Source: Superintendency of Banks (2022).

Note: N, S and W indicate degrees of latitude north, south and west, respectively.

For the variable Percentage share in each province of the SME loan portfolio in the total loan portfolio, the following hypothesis system was used as a starting point:

Null hypothesis (H_0): There are no significant differences in the percentage share in each province of the SME credit portfolio in the total credit portfolio between the two groups (2012 and 2022).

Alternative hypothesis (H_1): There is significant difference in the percentage share in each province of the SME credit portfolio in the total credit portfolio between the two groups.

Table 2 presents the results of the t-test for independent samples in two different scenarios: one where the variances are assumed to be equal and another that considers that they are not. Both tests are examined individually for 2012 and 2022 in Ecuador.

Table 1.

Levene's test for quality of variances and t-test for equality of means for the variable "Percentage share in each province of the SME loan portfolio in the total loan portfolio".

Percentage of the province's share of the SME loan portfolio at the national level									
	Levene's test		t-test for equality of means						
	F	Sig.	t	df	Sig. (bilateral)	Difference in averages	Standard error difference	95 % confidence interval of the difference	
								Lower	Upper
Equal variances are assumed	1,559	.218	-5,521	46	.000	-.0554083	.0100362	-.0756102	-.0352065
Equal variances are not assumed			-5,521	42,410	.000	-.0554083	.0100362	-.0756564	-.0351602

Source: Superintendency of Banks (2022).

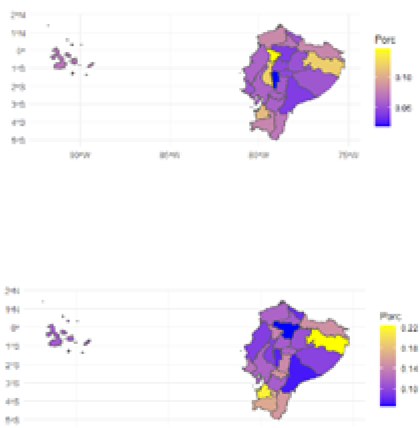
Levene's test for quality of variances yields a *p* value of 0.218, indicating that there is no significant evidence to reject equality of variances (equal variances are assumed). In the t-test for equality of means, the *p*-value is 0.000, so the null hypothesis is rejected. Thus, it is concluded that there is a significant difference between the two groups in the percentage share of the SME loan portfolio in the total loan portfolio in each province.

Information provided by the Superintendency of Banks (2022) reveals that, in the years 2012 and 2022, the proportion of the loan portfolio allocated to small and medium-sized enterprises (SMEs) in each province grew in 22 of the 24 provinces. The only exceptions were the provinces of Los Ríos and Santo Domingo de los Tsáchilas, where it decreased in relative terms. In 2012, this portfolio represented 5.45% of total credit, while in 2022 it increased to 9.87%.

The scenario described above is reflected in the heat maps, which show an increase in the share of the loan portfolio for small and medium-sized enterprises (SMEs) in the total loan portfolio for most Ecuadorian provinces between 2012 and 2022, specifically in the provinces of El Oro, Francisco de Orellana, Cañar, Chimborazo and Loja, but decreased in the provinces of Los Ríos and Santo Domingo de los Tsáchilas (See Figure 2).

Figure 2.

Heat maps of Ecuador for the variable "Percentage share in each province of the SME loan portfolio in the total loan portfolio".



Heat map year 2012
Heat map year 2022

Source: Superintendency of Banks (2022).

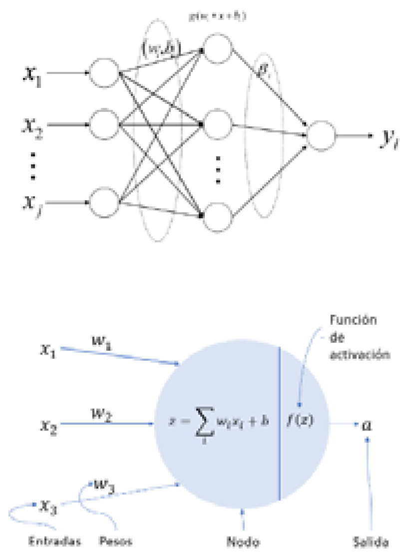
Note: N, S and W indicate degrees of latitude north, south and west, respectively.

During phase 2 of the research, the hybrid forecasting model combining the Holt-Winters method and the Extreme Learning Machine (ELM) network was implemented and adjusted and calibrated using historical data. A cross-validation was also performed and its performance was evaluated.

Aspects related to the structure of the model and the results obtained are presented below. Figure 3 shows the structure of the learning machine and the neuron.

Figure 3.

Structure of the extreme learning machine and the neuron.



Topology of the NNA Artificial Neuron

Source: Pang et al. (2021).

Neuron activation function:

$$y = \sum_{i=1} \beta_i g(w_i x_j + b) \quad (1)$$

This equation (1) is a function of the extreme learning machine; xj, refers to the amounts of total credits, SME credits and their respective variances where *j* = 1, 2, ... N, and refers to the analyzed variable, i indicates the number of nodes in the hidden layer; β is the output of the hidden layer and the weights of the hidden and the output layer; w is the input layer and the weights of the hidden layer, bis the bias of the input layer and the hidden layer, and is the activation function..

$$f(x_j) = \Sigma_{i=1} \beta_i g(w_i x_j + b) \quad (2)$$

According to the above formula, it can be seen that, in order to determine the total monthly approved amount of the loan portfolio, SME loans, β should be obtained. The input weight *wi* and bias *bi* are randomly generated in the learning machine, which will not affect the accuracy of the predetermined judgment. The function is Gaussian radial basis and is defined as follows (Huang et al., 2006):

$$g(w_i x_j + b) = e^{(-b_i \|x - w_i\|^2)} \quad (3)$$

For ease of derivation, the above linear equations can be simply expressed as:

$$y_t = H\beta \quad (4)$$

$$H(w_1, w_2, \ldots, w_L, x_1, x_2, \ldots, x_N, b_1, b_2, \ldots, b_L) = \begin{bmatrix} g(w_1 x_1 + b_1) & \ldots & g(w_L x_1 + b_L) \\ \vdots & & \vdots \\ g(w_1 x_N + b_1) & \ldots & g(w_L x_N + b_L) \end{bmatrix}$$

$$\beta = [\beta_1, \beta_2, \ldots, \beta_L]^T \quad (5)$$

To train the single-layer neural network, the input weight and the hidden layer bias are iterated according to the gradient algorithm, i.e., a programming problem with minimum error is obtained:

Huang *et al*. (2006) introduced the least squares norm technique to address this problem, ultimately turning it into a generalized inverse problem applicable for matrix resolution. The need for frequent adjustments in input weights () and biases) becomes obsolete. The extreme learning machine is responsible for determining the connection weight (β) between the hidden and output layers.

On many occasions, the number of training samples greatly exceeds the number of nodes in the hidden layer, making H a non-full rank matrix and β not unique. At this point, the generalized Moore-Penrose inverse (H) is employed to solve β. The calculation follows the method outlined by Huang *et al.* (2006):

$$\beta = H^+ y \quad (6)$$

Where H^+ is the generalized inverse or pseudoinverse matrix of matrix H. If the inverse H^T exists, H^+ can be expressed as indicated by Huang et al. (2006):

$$H^+ = (H^T H)^{-1} H^T \quad (7)$$

This can be obtained with β (Huang et al., 2006):

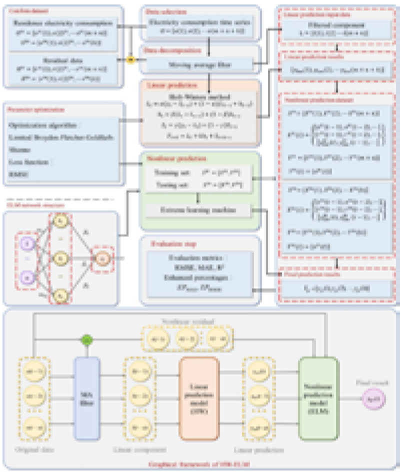
$$\beta = (H^T H)^{-1} H^T y \quad (8)$$

4.1. Structure of the model

In this research, the HW-ELM model is used, according to Liu et al. (2020). The applied structure is illustrated in Figure 4.

Figure 4.

Process of the proposed HW-ELM model



Source: Liu et al. (2020)

4.1.1 Data Decomposition

The data set of total loan portfolio, SMEs and their respective variations, denoted as O, is decomposed into two components: a linear stationary component (L) and a nonlinear wavelet residual (R). This decomposition is achieved by treating O as a time series:

$$O = [o(1), o(2), \ldots, o(m+n+h)] \quad (9)$$

Here, *m* represents the length of the linear prediction training set, *m + n* is the length of the nonlinear prediction training set, and *h* is the length of the test set. In this study, a moving average (MA) filter is used to extract the linear component (L) from the original O data set. The MA filter is known to be effective in reducing random noise while preserving sharp transitions:

$$L = [l(1), l(2), \ldots, l(m+n+h)] \quad (10)$$

4.1.2 Linear Prediction

The nonlinear wavelet residual (R) is calculated as the difference between O and L:

$$R = O - L \quad (11)$$

$$R = [r(1), r(2), \ldots, r(m+n+h)] \quad (12)$$

The linear prediction model is built using the Holt-Winters (HW) method, which is chosen because it is suitable for modeling linear data series.

4.1.2.1 Holt-Winters method

Depending on the seasonality of the data, two types of seasonality are considered: "multiplicative" and "additive". The predicted value F_{t+k} at time *t+k* is determined by the level (L_t), the data value (Y_t), the trend (b_t) and the seasonal component (S_t) at time t and at time t+k. The method is parameterized by smoothing factors (α, β, γ) and the length of the seasonal cycle (*s*).

An optional HW model adds a seasonal equation to the forecast:

$$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (13)$$

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (14)$$

$$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-s} \quad (15)$$

$$F_{t+k} = L_t + kb_t + S_{t+k-s} \quad (16)$$

4.1.2.2 Linear prediction model

The Holt-Winters model parameters are optimized using the constrained Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) method, with the root mean square error (RMSE) as the loss function. The L-BFGS method is selected for its fast convergence and low memory consumption.

The HW model is developed using stationary linear components and can be represented as follows:

$$y_{hw}(t) = g(l(t-1), l(t-2), \ldots, l(t-s), op, op, op) \quad (17)$$

Here, is the HW prediction result at time t, *g* is the prediction function, *s* is the length of the seasonal cycle, and *op, op,* and *op* are the optimized parameters of the HW model.

4.1.3. Non-linear prediction

The nonlinear prediction model is established using an Extreme Learning Machine (ELM) network, which is a single-layer hidden feedforward neural network known for its generalization capability and training speed.

4.1.3.1 Extreme machine learning

ELM networks differ from other machine learning algorithms in that they randomly select hidden thresholds during training and analyze the output weights without iterative computation. The result is significantly faster training speed than traditional neural networks. The ELM network is used to model the nonlinear component of the data.

$$\sum_{i=1}^{L} \beta_i g(W_i x_i + b_i) = o_j, j = 1, \dots N \quad (18)$$

4.1.3.2 Nonlinear Prediction Model

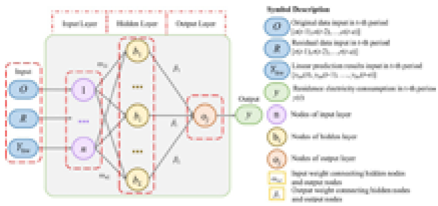
The performance of the ELM model is always optimized by selecting the number of hidden layer nodes. In this paper, the rank optimization method is used to obtain the optimal number of hidden layer nodes.

First, the selection range of the number of nodes in the hidden layer is determined by experience. The selection range used is from 5 to 60. Then, ELM models are built with each number of hidden layer nodes in the selected range. The RMSE is used to evaluate the performance of each. The number of hidden layer nodes of the ELM with the best performance is the optimal parameter.

Figure 5 shows the structure of the nonlinear prediction model. At the *t*-th period, the results Y (t, t-1, t-2, t-α) of linear prediction forecast, the nonlinear residual series R (t, t-1, t-2, t-α), and the original time series O (t, t-1, t-2, t-α) are combined into the ELM network

Figure 5.

Structure of the nonlinear prediction model.



Sourse: Liu et al. (2020)

According to Liu et al. (2020), a training set larger than that of the linear prediction model is chosen to train the nonlinear prediction one. This is done as follows:

$$\begin{cases} O^{tr} = [o^{tr}(1), o^{tr}(2), \dots, o^{tr}(m+n)] \\ R^{tr} = [r^{tr}(1), r^{tr}(2), \dots, r^{tr}(m+n)] \\ Y_{hw}^{tr} = [y_{hw}^{tr}(1), y_{hw}^{tr}(2), \dots, y_{hw}^{tr}(m+n)] \end{cases} \quad (19)$$

$$\begin{cases} S^{tr} = [X^{tr}, Y^{tr}] \\ X^{tr} = [x^{tr}(t-1), x^{tr}(t-2), \dots, x^{tr}(m+n)] \\ x^{tr}(t) = \begin{cases} [o^{tr}(t-1), o^{tr}(t-2), \dots, o^{tr}(t-\alpha)], \\ [r^{tr}(t-1), r^{tr}(t-2), \dots, r^{tr}(t-\alpha)], \\ [y_{hw}^{tr}, y_{hw}^{tr}(t-1), y_{hw}^{tr}(t-2), \dots, y_{hw}^{tr}(t-\alpha)] \end{cases} \\ Y^{tr} = [Y^{tr}(1), Y^{tr}(2), \dots, Y^{tr}(m+n)] \\ y^{tr}(t) = [o^{tr}(t)] \end{cases} \quad (20)$$

Where is the original time series for training, is the residual for training, is the training output series of the linear prediction model, *m+n* is the size of the training set. On the other hand, for the nonlinear prediction model is the training result, is the training input, is the training output and α is the number of backward steps of the input features.

The test suite of the nonlinear prediction model is divided as follows:

$$\begin{cases} O^{te} = [o^{te}(1), o^{te}(2), \dots, o^{te}(h)] \\ R^{te} = [r^{te}(1), r^{te}(2), \dots, r^{te}(h)] \\ Y_{hw}^{te} = [y_{hw}^{te}(1), y_{hw}^{te}(2), \dots, y_{hw}^{te}(h)] \end{cases} \quad (21)$$

$$\begin{cases} S^{te} = [X^{te}, Y^{te}] \\ X^{te} = [X^{te}(t-1), X^{te}(t-2), \ldots, X^{te}(h)] \\ X^{te}(t) = \begin{cases} [o^{te}(1), o^{te}(2), \ldots, o^{te}(t-\alpha)], \\ [r^{te}(1), r^{te}(2), \ldots, r^{te}(t-\alpha)], \\ [y^{te}_{hw}, y^{te}_{hw}(t-1), y^{te}_{hw}(t-2), \ldots, y^{te}_{hw}(t+\alpha)] \end{cases} \\ Y^{te} = [Y^{te}(1), Y^{te}(2), \ldots, Y^{te}(m+n)] \\ Y^{te}(t) = [o^{te}(t)] \end{cases} \quad (22)$$

Where represents the original time series used in the tests, is the residual corresponding to the tests, is the series of results of the linear prediction model in the tests, *h* indicates the size of the test set. With respect to the nonlinear prediction model, is the test set used, refers to the test input, *te* is the result obtained during testing of that model, and α indicates the number of backward steps of the features introduced into it. The set of forecast results is obtained from the output of the nonlinear prediction model and the size of the test set, , is used to evaluate it.

The series of forecast results *Ypr* is obtained from the output of the nonlinear prediction model:

$$Ypr = [ypr(1), ypr(2), \ldots, ypr(h)] \quad (23)$$

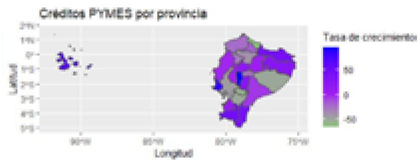
The HW develops a linear prediction model to estimate the stationary component of the data set to be evaluated. By considering the nonlinear residual values and the results of the linear prediction model, the ELM develops the nonlinear prediction model. At this point, the HW-ELM is established by taking advantage of the unique strengths of both, which is capable of accurate forecasts. Given the characteristics of the HW and ELM methods, the proposed model can be developed with a relatively small training set and short training time. All these features of the HW-ELM model are verified in the process.

4.2. HW-ELM model results

The HW-ELM model indicates a drop in SME lending at the national level between March/2015 and September/2021 (purple circle); the most affected provinces are Manabí, Morona, Imbabura, Esmeraldas, Tungurahua, Santo Domingo de los Tsáchilas, Pichincha, Guayas, Azuay, Pastaza, Cañar and Carchi, which present negative growth rates in monthly amounts, according to data from the Superintendency of Banks (2022), and are shown in the heat map with gray and light purple color; in the rest of the provinces positive growth rates were obtained for the referred indicator. The trend of the forecast up to 2028 can be seen in Figure 6.

Figure 6.

Results of the combined Holt-Winter and ELM model for the variable "SME loan portfolio January/2010 to December/2028", and heat map of Ecuador of the average growth rate of SME loans by province, from March/2015 to September/2021.



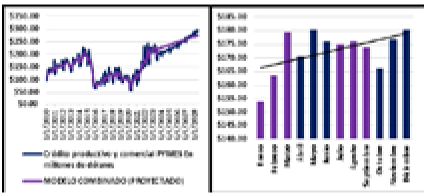
Results of the HW-ELM model heap map march/2015 to september/2021

Sourse: Superintendency of Banks (2022).

As shown in Figure 7, during the months of March, April, May, June, July, August and December, the figures are above the trend line. It is especially noteworthy that the second and third quarters of each year are the periods of greatest growth in lending to small and medium-sized enterprises (SMEs).

Figure 7.

Forecast of the combined Holt-Winter and ELM model for the variable "SME loan portfolio" and histogram on the average amount of loans (January/2010 to December/2028)..



Forecast HW-ELM Model
Average amounts granted in SME loans

Sourse: Superintendency of Banks (2022)

Error metrics are fundamental to evaluate and compare different forecasting models, such as Holt-Winter (HW), Extreme Learning Machine (ELM) and the HW-ELM combination. Each of the metrics plays an important role in the evaluation of these models:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}[y(t) - Y(t)]^2} \quad (24)$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}[y(t) - Y(t)] \quad (25)$$

$$R^2 = 1 - \frac{\sum_{t=1}^{n}[y(t)-Y(t)]^2}{\sum_{t=1}^{n}[y(t)-\bar{y}(t)]^2} \quad (26)$$

$$\%MAE = \frac{1}{n}\sum_{t=1}^{n}\frac{y(t)-Y(t)}{y(t)} \quad (27)$$

The RMSE (Root Mean Square Error) (Eq. 24) is an essential metric in forecasting analysis. What it does is to measure the square root of the average squared difference between the actual values (denoted as y(t)) and the predicted values (represented as Y(t)). In other words, it shows how close the model is to the actual data. If the RMSE is low, it means that the model fits the actual data very well. This metric is particularly useful for penalizing larger errors, as the differences are squared, which means that larger errors have a significantly larger impact on the result (Ahmar *et al*., 2021).

On the other hand, the MAE (Mean Absolute Error) (Eq. 25) is also a valuable metric in forecast analysis. Unlike RMSE, MAE measures the average absolute difference between the actual values (*y(t))* and the predicted values (*Y(t)*) and is less sensitive to outliers compared to RMSE, which makes it suitable when it is desired to understand the average error in the same unit as the original data (Atoyebi *et al.,* 2023).

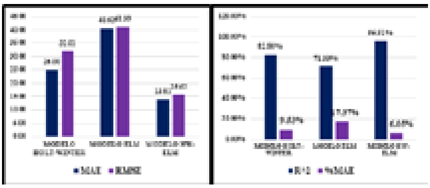
The (Coefficient of Determination) indicator (Eq. 26) is crucial to assess how much variation in the data is explained by the model. This coefficient measures the proportion of the total variation in the actual values (*y(t)*) that is explained by the predicted values (*Y(t)*). A higher value of indicates that the model fits the actual data better, meaning that it is able to explain more of the variability in the actual data (Liu *et al*., 2020).

Finally, the %MAE (Mean Percentage Absolute Error) (Eq. 27) is a useful metric for evaluating error in terms of its relative importance rather than its absolute values. This indicator is expressed as a percentage of the actual value (*y(t)*), which can be especially convenient when the magnitudes of the predicted and actual values vary significantly (Sokolov-Mladenović *et al*., 2016).

Figure 8 shows that the HW-ELM combination model presents the lowest error values and stands out as the most appropriate in situations where the magnitudes of the predictions and the actual values undergo significant changes.

Figure 8.

Model error metrics for the SME loan portfolio variable, from January/2010 to December/2028.



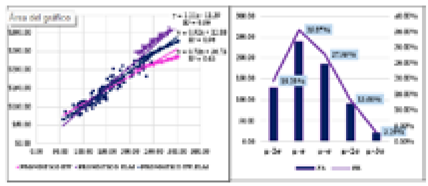
Model error metrics (a)
Model error metrics (b)

Sourse: Superintendency of Banks (2022).

Figure 9 shows a high linear association between the observed data and the forecast provided by the Holt-Winter model, with a coefficient of determination R^2 of 0.93.

Figure 9

Descripción experimental de la variable cartera de crédito PYMES enero/2010 a diciembre/2028.



Correlation between observed and forecast data Frequency of forecasts

μ-2σ	μ-σ	μ+σ	μ+2σ	μ+3σ
$50,56	$111,53	$172,45	$233,46	355,39

Sourse: Superintendency of Banks (2022).

However, when compared to other models, the HW-ELM demonstrates slightly better performance, with an R^2 of 0.96, while the ELM also performs well, with an R^2 of 0.95.

When the forecasts of the three models are combined, a leftward skew in the distribution of errors is observed, implying that the predicted values tend to be slightly lower than the actual values. This is reflected in the kurtosis, which has a value of -0.74. The symmetry coefficient was positive, with a value of 0.42, and indicates that the tail of the error distribution is shifted to the right compared to a symmetric distribution.

DISCUSSION OF RESULTS

The geospatial analysis provided a broader view at the provincial level of the evolution of SME commercial-productive credit in Ecuador. It also made it possible to understand how this indicator behaves at the national level and what are the reasons for the drop in credit to SMEs.

The 2012 and 2022 heat maps showed that the SME loan portfolio at the national level, in the last 10 years, continues to be concentrated in provinces such as Guayas and Pichincha, followed by the provinces of Azuay, Manabí and El Oro. This situation explained by Urdaneta and Borgucci (2021), who point out that the cantons Guayaquil and Quito, capitals of these provinces, concentrated between 2007 and 2017 40.53 % of the gross domestic product (GDP). Likewise, of all the companies registered in Ecuador, most are located in the cities of Quito and Guayaquil. This includes 50 % of small companies, 53 % of medium-sized company A, 56 % of medium-sized company B and 64 % of large companies (Urdaneta and Borgucci, 2021).

According to the Superintendency of Banks (2022), in the years 2012 and 2022, although the proportion of the SME loan portfolio in each province grew in 22 of the 24 provinces, Los Ríos and Santo Domingo de los Tsáchilas showed a decrease in relative terms. This scenario is due to a complex interplay of economic and regional factors affecting SME lending in these specific areas, which require detailed analysis for a better understanding.

First, local economic dynamics play a key role in this trend, since over the course of a decade, provinces can experience significant changes in their economic activity. In the case of Los Ríos, a contraction is observed in economic sectors such as real estate activities, public administration, defense, compulsory social security schemes, animal husbandry, sugar processing and financing of insurance schemes, except social security, according to data from the provincial accounts for the real sector of the Central Bank of Ecuador in 2020, compared to 2010.

Similarly, in the province of Santo Domingo de los Tsáchilas, reductions were recorded in sectors such as animal husbandry, accommodation and food services, processing of oils and fats of vegetable and animal origin, processing of other food products, processing of mill products, bakery and noodles, manufacture of machinery and equipment, manufacture of paper and paper products, private households with domestic service, fishing and aquaculture (except shrimp), and transport and storage. This contraction may have contributed to a decrease in business activity and, consequently, to a lower demand for credit in these provinces.

In addition, the composition of the industrial sector in these provinces may differ from other areas, which also impacts the need for financing. If the regions rely heavily on sectors that do not typically use credit, such as agriculture, banana, coffee and cocoa cultivation, in the case of Los Rios province, which increased from 24% to 32% of provincial GDP, this could explain the lower demand for SME loans.

The contraction of fundamental economic activities for the Ecuadorian economy also impacts innovation capacity, entrepreneurial orientation, flexibility and environmental factors in small and medium-sized enterprises (SMEs) in the chemical and pharmaceutical sector in Ecuador, as indicated by the study conducted by Anzules and Novillo (2023).

The credit policies of local financial institutions, as well as the effects of economic events and public investment, can also influence the availability and access to credit for companies. Finally, cultural and social factors, such as attitudes towards indebtedness and business investment, may also vary in different territories and have an impact on the demand for credit.

The deterioration in the economic environment affects corporate social responsibility, specifically with regard to financial inclusion in the Ecuadorian private banking system, as suggested by Acosta (2019), and hinders access to the poorest and most vulnerable segments of the population to financial services and products that meet their needs in a responsible, sustainable and profitable manner.

The research contribution is undeniable in terms of the combination of econometric models and neural network applications, as pointed out by Liu et al. (2020). In this case, 163 values observed during the period January/2010 and July/2023 were used, with the purpose of making a forecast of 60 values for the period August/2023 to July/2028, which is equivalent to a forecast horizon of 5 years.

The HW-ELM model indicated a drop in the granting of SME loans at the national level between March/2015 and September/2021, which was due to the contraction of economic activities in that period, such as oil and mining, manufacturing and construction, which represent 29.35% of the total GDP of the Ecuadorian economy, according to figures from the Central Bank (2020), while these provinces represent 79.95% of the GDPR and 87.59% of the amount of SME loans granted by the public-private financial system of Ecuador. This corroborates the findings of Álvarez et al. (2023) regarding territorial inequalities in the access and use of financial services in this country, where private banks show high levels of financial inclusion in provinces with higher socioeconomic status.

The months of March, April, May, June, June, July, August and December record figures that exceed the trend line, while the second and third quarters of each year are the periods with the highest SME lending. The result indicates an efficient forecast of the HW-ELM Model and corroborates the effectiveness of the model, according to Liu et al. (2020).

The lower error values of the HW-ELM combination model make it stand out as the most suitable for forecasts whose actual values undergo noticeable changes. This model excels at explaining a substantial proportion of the total variation in actual values ($y(t)$) through its forecasts ($Y(t)$), implying that it is highly capable of addressing and understanding a considerable portion of the variability present in the data. Furthermore, it is found to be an optimal fit to the real data, and its robustness to outliers makes it the most efficient choice when seeking to evaluate the average error on the same scale as the original data.

The high linear association between the observed data and the forecast provided by the Holt-Winter model (coefficient of determination R2 of 0.93) suggests that this model is able to explain 93 % of the variability in the observed data, indicating a good fit. However, relative to other models, both the HW-ELM and ELM also perform well, so both are capable of providing accurate forecasts.

Combining the forecasts of the three models shows a kurtosis of -0.74, which suggests that the distribution of the errors is relatively flat compared to a normal distribution. The positive symmetry coefficient (0.42) indicates that there is a higher concentration of positive errors in the right tail of the distribution, implying that, on average, the forecasts tend to be slightly optimistic compared to the actual values.

CONCLUSIONS

It is concluded that there is a persistent concentration of the credit portfolio in provinces such as Guayas and Pichincha, supporting the idea that financial centers such as Guayaquil and Quito play a key role due to their significant contribution to the national GDP.

The HW-ELM model shows a decrease in SME lending at the national level between March 2015 and September 2021, associated with the contraction in key economic sectors. The combination of models provided accurate forecasts showing a high linear association with the observed data, thus, the application of econometric models and neural networks provided valuable information on the allocation of financial resources in Ecuador.

The results emphasize the importance of efficiency in the financial and economic development of the country, especially in relation to the allocation of credit to SMEs and the crucial role of larger firms in the economy (Feijó et al., 2023).

Previous studies highlight the scope for efficiency improvements in most banks in Ecuador (Proaño and Feria, 2022). Larger companies tend to receive more substantial allocations of financial resources, especially in advanced stages of production. This translates into higher levels of liquidity and profitability, contributing to the strengthening of asset and equity valuation (Bacuilima et al., 2023). In the Ecuadorian economic context, larger companies receive larger allocations of financial resources through productive credit granted by banking institutions, justified by the need for significantly higher capital investment compared to medium or small companies, especially in advanced stages of production over time (Amadasun and Mutezo, 2022).

The investment goes to highly skilled labor, with high costs, as well as the acquisition of machinery and technology to improve productivity (Amadasun and Mutezo, 2022). The productivity of a firm is closely related to the efficient allocation of production factors, such as capital, labor and technology, implying that the value added per additional unit of production factors is considerably higher in large firms compared to medium or small ones (Attar, 2021).

Productivity benefits are reflected in the financial statements of the companies, evidencing higher levels of liquidity and short-term profitability in terms of equity and assets. The higher amount of reinvested earnings contributes to strengthening the valuation of assets and equity, creating opportunities to obtain additional financial resources (Bacuilima *et al.,* 2023). In a macroeconomic context, this process resembles capital accumulation, with capital endowment per capita being a crucial indicator to measure the wealth of a society.

REFERENCES

Acosta, G. (2019). Responsabilidad social empresarial: inclusión financiera en el sistema bancario privado ecuatoriano. *Visión de Futuro, 23*(1), 1-11.

Ahmar, A., Singh, P., & Thanh, N. (2021). Prediction of BRIC Stock Price Using ARIMA, SutteARIMA, and Holt-Winters. *Tech Science Press, 70*(1), 523-534. doi:10.32604/cmc.2022.017068

Almazrouee, A., Almeshal, A., Abdulrahman, A., Alenezi, M. R., & Alhajeri, S. (2020). Long-Term Forecasting of Electrical Loads in Kuwait Using Prophet and Holt–Winters Models. *Applied Sciences*, 1-17.

Álvarez, J., Cabrera, P., & Jácome, H. (2023). Territorial inequalities in financial inclusion: A comparative study between private banks and credit unions. *Socio-Economic Planning Sciences*.

Amadasun, D., & Mutezo, A. (2022). Infuence of access to fnance on the competitive growth of SMEs in Lesotho. *Journal of Innovation and Entrepreneurship*, 1-20.

Anzules, W., & Novillo, S. (2023). Innovation Capacity, Entrepreneurial Orientation, and Flexibility: An Analysis from Industrial SMEs in Ecuador. *Sustainability*, 1-24.

Apichatibutarapong, S. (2015). Business forecasting technique on mobile devices by using R-Programming. *Procedia - Social and Behavioral Sciences, 197*, 1377-1382. doi: doi: 10.1016/j.sbspro.2015.07.081

Atoyebi, S. B., Olayiwola, M. F., Oladapo, J. O., & Oladapo, D. I. (2023). Forecasting Currency in Circulation in Nigeria Using Holt-Winters Exponential Smoothing Method. *South Asian Journal of Social Studies and Economics, 20*(1), 25-41. doi:10.9734/SAJSSE/2023/v20i1689

Attar, M. A. (2021). Growth, distribution and dynamic inefficiency in Turkey: An analysis of the naïve neoclassical theory of capital. *Structural Change and Economic Dynamics, 59*, 20-30.

Bacuilima, E., Morocho, J., Aguirre, J., Coronel, K., & Mora, P. (2023). Financing Ecuadorian Social Enterprises: What Is the Role of Impact Investment? *Sustainability*, 1-19.

Bairagi, V., & Munot, M. (2019). *Research Methodology: A Practical and Scientific Approach.* Boca Ratón, Florida, Estados Unidos: CRC Press.

Coaquira, M., Tudela, J., & Jiménez, M. (2023). Evaluación comparativa regional: índice sintético de desarrollo regional (IDR) para Perú. *Revista Desarrollo y Sociedad*, 109-157.

Deina, C., Prates, M., Alves, C., Martins, M., Trojan, F., Stevan, S., & Siqueira, H. (2021). A methodology for coffee price forecasting based on extreme learning machines. *Information Processing in Agriculture*(9), 556-565. doi:https://doi.org/10.1016/j.inpa.2021.07.003

Díaz, R., Bravo, L., Alatorre, L., & Sánchez, E. (2014). Análisis geoespacial de la interacción entre el uso de suelo y de agua en el área peri-urbana de Cuauhtémoc, Chihuahua. Un estudio socioambiental en el norte de México. *Investigaciones Geográficas, Boletín del Instituto de Geografía, UNAMISSN 0188-4611*(83), 116-130. doi:10.14350/rig.32694

Dritsaki, M., & Dritsaki, C. (2021). Comparison of the Holt-Winters Exponential Smoothing Method with ARIMA Models: Forecasting of GDP per Capita in Five Balkan Countries Members of European Union (EU) Post COVID. *Scientific Research Publishing Inc*, 1972-1998.

Feijó, N., Ceular, N., & Navajas, V. (2023). Behavioral Patterns That Influence the Financing Choice Models of Small Enterprises in Ecuador through Latent Class Analysis. *Sustainability, 15* , 1-17. doi:https://doi.org/10.3390/su15086790

Hidayat, A., & Darmawan, P. (2023). ARIMA Model and Holt Winters Seasonal Smoothing Accuracy for Stock Price Prediction. *Journal of Actuarial, Finance and Risk Management (JAFRM), 2*(1), 10-19. doi: https://doi.org/10.25077/jafrm.2.1.10-19

Huang, G.-B., Zhu, Q.-Y., & Siew, C.-K. (2006). Extreme learning machine: Theory and applications. *Neurocomputing*, Volume 70, Issues 1–3, 489-501. doi:https://doi.org/10.1016/j.neucom.2005.12.126

Karadžić, V., & Pejović, B. (2021). Inflation forecasting in the Western Balkans and EU: A comparison of Holt-Winters, ARIMA and NNAR models. *Amfiteatru Economic, 23*(57), 517-532.

Li, H., Bai, J., & Li, Y. (2019).). Anovel secondary decomposition learning paradigm with kernel extreme learning machine for multi-step forecasting of container throughput. *Physical A: Statistical Mechanics and its Applications, 534, 122025.* doi:https://doi.org/10.1016/j.physa.2019.122025.

Lima, S., Gonçalves, M., & Costa, M. (2019). Time series forecasting using Holt-Winters exponential smoothing: An application to economic data. *Proceedings of the International Conference of Computational Methods in Sciences and Engineering 2019 (ICCMSE-2019).* Published by AIP Publishing. 978-0-7354-1933-9. doi:doi.org/10.1063/1.5137999

Liu, C., Sun, B., Zhang, C., & Li, F. (2020). A hybrid prediction model for residential electricity consumption using holt- winters and extreme learning machine. *Applied Energy, 275*, 1-15.

Longley, P., Goodchild, M., Maguire, D., & Rhind, D. (2015). *Geographic Information Science and Systems.* United State of America: WILEY.

Makridakis, S., Spiliotis, E., & & Assimakopoulos, V. (2020). The M4 Competition: 100,000 time series and 61 forecasting methods. *International Journal of Forecasting*, 54-74. doi:https://doi.org/10.1016/j.ijforecast.2019.04.014

Mejía, E., & Gonzales, S. (2019). Predicción del consumo de energía eléctrica residencial de la Región Cajamarca mediante modelos Holt -Winters. *Ingeniería Energética, 40*(3), 181-191.

Naim, I., Mahara, T., & Rahman, A. (2018). Effective short-term forecasting for daily time series with complex seasonal patterns. *Procedia Computer Science, 132*, 1832-1841. doi:. https://doi.org/10.1016/j.procs.2018.05.136

Pang, S., Hou, X., & Xia, L. (2021). Borrowers' credit quality scoring model and applications, with default discriminant analysis based on the extreme learning machine. *Technological Forecasting & Social Change, 165*. doi:https://doi.org/10.1016/j.te

Pleños, M. (2022). Time Series Forecasting Using Holt-Winters Exponential Smoothing: Application to Abaca Fiber Data. Problems of World Agriculture. *Scientific Journal Warsaw University of Life Sciences, 22*(2), 17-29. doi:10.22630/PRS.2022.22.2.6

Proaño, B., & Feria, J. (2022). Are Ecuadorian banks enough technically efficient for growth? A clinical study. *WILEY*, 1-19.

Sokolov-Mladenović, S., Milovančević, M., & Mladenović, I. (2016). Sokolov-Mladenović Economic growth forecasting by artificial neural network with extreme learning machine based on trade, import and export parameters. *Sokolov-Mladenović, S., Milovančević, M., & Mladenović, I. (2016). Economic growth forecasting by artificial neural network with extreme Computers in Human Behavior*(65), 43-45. doi:10.1016/j.chb.2016.08.014

Sulaiman, A., & Juarna, A. (2021). PERAMALAN TINGKAT PENGANGGURAN DI INDONESIA MENGGUNAKAN METODE TIME SERIES DENGAN MODEL ARIMA DAN HOLT-WINTERS. *Jurnal Ilmiah Informatika Komputer, 26*(1), 13-28.

Urdaneta, A. J., & Borgucci, E. V. (2021). Economías de aglomeración y externalidades negativas en Ecuador, periodo 2007-2017. *Cuadernos de Economía, 40*(82), 165-191.

Wang, J., Athanasopoulos, G., Hyndman, R. J., & Wang, S. (2018). Crude oil price forecasting based on internet concern using an extreme learning machine. *International Journal of Forecasting., 34*(4), 665-677. doi:https://doi.org/10.1016/j.ijforecast.2018.03.00

Winters, P. (1960). Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science, 6*(3), 324-342.

Zhou, W., Tao, H., & Jiang, H. (2022). Application of a novel optimized fractional grey Holt-Winters model in energy forecasting. *Sustainability, 14*(5), 1-18. doi:https://doi.org/10.3390/su14053118