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EVALUATING THE IMPACT OF ESG AND DECARBONIZATION METRICS ON STOCK PRICE PREDICTION

ESG ve Karbon Azaltma Metriklerinin Hisse Senedi Fiyat Tahmini Üzerindeki Etkisinin Değerlendirilmesi

Çiğdem YERLİ[*]

Abstract

This study investigates the effectiveness of incorporating sustainability metrics, specifically ESG scores and corporate decarbonization targets, into stock price prediction models using LSTM neural networks. The aim is to assess whether these non-financial indicators enhance predictive accuracy across different sectors. The analysis focuses on five BIST 100 companies from diverse industries, using data spanning from 1 January 2020 to 19 March 2025. Three model configurations were tested: one based solely on historical stock prices, one with added ESG scores, and another with decarbonization data. The data were preprocessed using normalization techniques and split into training and testing sets to ensure robust model performance. Results were evaluated using MAE, MSE, and RMSE. Findings reveal that sustainability metrics improved prediction accuracy primarily in emission-intensive sectors like aviation (THYAO) and oil refining (TUPRS), while offering limited or even negative impact in others, such as defense (ASELS). Surprisingly, steel producer EREGL showed only modest gains despite expectations of higher sensitivity. Overall, the study shows that the influence of sustainability metrics on financial forecasting varies by sector. It underscores the importance of tailoring input features to fit the unique dynamics of each industry.

Anahtar Kelimeler: ESG, Decarbonization, Financial Forecast, LSTM

JEL Kodları: C45, C53, Q56

Öz

Bu çalışma, sürdürülebilirlik metriklerinin, özellikle ESG puanları ve kurumsal karbon azaltım hedeflerinin, LSTM sinir ağları kullanılarak yapılan hisse senedi fiyat tahmin modellerine entegre edilmesinin etkinliğini incelemektedir. Amaç, bu finansal olmayan göstergelerin farklı sektörlerde tahmin doğruluğunu artırıp artırmadığını değerlendirmektir. Analiz, 1 Ocak 2020 ile 19 Mart 2025 tarihleri arasındaki veriler kullanılarak, çeşitli sektörlerden beş BIST 100 şirketine odaklanmaktadır. Üç farklı model yapısı test edilmiştir: yalnızca geçmiş hisse senedi fiyatlarına dayalı bir model, ESG puanlarının eklendiği bir model ve karbon azaltım verilerini içeren model. Veriler, normalizasyon teknikleriyle ön işleme tabi tutulmuş ve güçlü bir model performansı sağlamak amacıyla eğitim ve test setlerine ayrılmıştır. Sonuçlar, MAE, MSE ve RMSE ölçütleri kullanılarak değerlendirilmiştir. Bulgular, sürdürülebilirlik metriklerinin özellikle havacılık (THYAO) ve petrol rafinajı (TUPRS) gibi emisyon yoğun sektörlerde tahmin doğruluğunu artırdığını, savunma sanayi (ASELS) gibi diğer bazı sektörlerde ise sınırlı veya olumsuz etkiler gösterdiğini ortaya koymaktadır. Beklentilere rağmen, çelik üreticisi EREGL yalnızca sınırlı düzeyde iyileşme göstermiştir. Genel olarak, çalışma sürdürülebilirlik ölçümlerinin finansal tahmin üzerindeki etkisinin sektöre göre değiştiğini göstermektedir. Her sektörün benzersiz dinamiklerine uyacak şekilde girdi özelliklerinin uyarlanmasının önemini vurgulamaktadır.

Keywords: ESG, Karbon Azaltım, Finansal Tahmin, LSTM

JEL Codes: C45, C53, Q56

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1. Introduction

Sustainability has become an important global priority, reshaping how businesses approach long-term strategies. Growing emphasis on sustainable development has led companies to integrate Environmental, Social, and Governance (ESG) criteria into their performance evaluations (Egorova et al., 2022; Lee et al., 2023). These metrics help assess a firm's environmental impact, ethical standards, and leadership quality, offering a clear framework to measure its commitment to sustainable operations (Lee et al., 2024). Companies that adopt environmentally friendly practices, prioritize social welfare, and maintain transparent governance tend to earn higher investor trust. Studies suggest that high ESG performance frequently correlates with higher stock valuations, as stakeholders view these initiatives as reducing risk and supporting long-term profitability (Aybars et al., 2019). This relationship motivates companies to enhance their sustainability efforts, fostering closer collaboration between businesses and investors while advancing shared economic and ethical objectives (In et al., 2019).

Sustainability and ESG metrics are increasingly influencing investor behavior in financial analysis. This change highlights the importance of incorporating ESG factors into evaluation models, effectively linking responsible corporate actions with long-term investment strategies. Employing ESG indices to forecast benchmarks like the S&P 500 represents a new approach that acknowledges ESG considerations in guiding investment decisions (Alareeni and Hamdan, 2020). The increasing interest in how ESG performance influences equity valuation highlights the growing significance of ESG metrics in today's financial markets (Kiesel and Lücke, 2019; Scatigna et al., 2021).

The financial sector is key to this transition, as it incorporates ESG factors into its investment decision-making processes. This approach supports ongoing investments in sustainable projects and initiatives (European Commission, 2025). According to the OECD, integrating ESG factors into financial evaluations is increasingly shaped by urgent global challenges, including climate change, social inequality, corporate governance standards, and ethical business practices (Boffo and Patalano, 2020). ESG indicators play a crucial role, and their integration offers significant potential. This research adopts a comprehensive analytical approach to thoroughly examine the synergy created by combining these factors.

In recent years, CO^2 emission targets and corporate awareness of carbon footprints have emerged as key topics in academic research, reflecting a broader shift toward environmental accountability. These indicators are now central to evaluating corporate sustainability, alongside other environmental metrics. At the policy level, governments are taking a more active role in regulating emissions. The European Union, for instance, has introduced measures such as the EU Green Deal and the "Fit for 55" initiative, both designed to reduce emissions from major corporations through a mix of regulation and taxation. In the USA, legislation like the Clean Air Act enforces similar standards. As a result, environmental compliance is no longer optional but a binding obligation for firms. In this evolving regulatory landscape, understanding the influence of decarbonization targets on market behavior is becoming increasingly important. Investigating the role of emission goals in financial performance can help bridge the gap between sustainable investment strategies and market outcomes, supporting more informed and responsible investment decisions.

The emergence of machine learning has significantly improved the forecasting of financial markets. An extensive body of literature highlights machine learning's superior predictive capabilities compared to traditional forecasting methods. By incorporating historical stock data and environmental metrics, machine learning models may facilitate accurate predictions of future stock price movements. Consequently, investors can strategically allocate capital to promote responsible business practices, fostering a socially and environmentally sustainable investment landscape.

Given the increasing importance of ESG factors in investment decision-making and corporate strategy, a substantial body of literature has emerged examining the relationship between ESG performance and firm financial outcomes. However, the findings remain fragmented and inconclusive. A number of studies suggest a positive correlation, indicating that strong ESG performance contributes to improved firm value and financial performance (Yoon et al., 2018; Deng and Cheng, 2019; Berg et al., 2022; Lapinskienė et al., 2023). In contrast, other researchers report a negative relationship, implying that ESG investments may divert resources from core profit-generating activities (Brammer et al., 2006; Di Tommaso and Thornton, 2020; Luo, 2022). Still, some studies find no statistically significant correlation between ESG metrics and corporate financial performance, suggesting the effects may be context-dependent or influenced by methodological choices (Halbritter and Dorfleitner, 2015; La Torre et al., 2020).

In addition to these conflicting findings, a critical gap exists in the geographical scope of existing research. Most empirical studies have concentrated on firms in developed markets, where ESG disclosure standards are more established and regulatory frameworks are more consistent (Brammer et al., 2006; Di Tommaso and Thornton, 2020; Luo, 2022; Berg et al., 2022; Lapinskienė et al., 2023). In contrast, relatively few studies have examined ESG performance in emerging economies, where institutional environments, investor behavior, and ESG implementation practices can differ significantly (Yoon et al., 2018; Deng and Cheng, 2019). This imbalance limits the generalizability of existing findings and overlooks important regional dynamics.

This study directly addresses a critical gap in existing literature by evaluating the predictive value of ESG metrics, particularly corporate decarbonization indicators, within the context of an emerging market. To this end, we propose a novel methodological approach that integrates these sustainability variables into advanced machine learning frameworks. Specifically, we utilize Long Short-Term Memory (LSTM) neural networks, which are well-suited for modeling the nonlinearities and temporal dependencies characteristic of financial time series data. Our empirical setting is the Turkish stock market, which offers a compelling case study due to Turkey's status as a prominent emerging economy undergoing significant transitions in both its sustainability practices and capital market development.

The primary aim of the study is to assess whether the incorporation of environmental indicators improves the forecasting performance of LSTM-based trading models. In doing so, we contribute to the methodological advancement of ESG-based financial modeling and provide practical insights for investors and finance professionals seeking to integrate sustainability considerations into quantitative trading strategies. Furthermore, we examine which stocks exhibit the greatest sensitivity to ESG-related data, offering a nuanced understanding of how sustainability information may influence financial market behavior in emerging economies.

The remainder of this paper is structured as follows. First, a comprehensive literature review is presented. Next, the data and methodology employed are described in detail, followed by an overview of the proposed LSTM model. The subsequent sections provide an analysis of the results, concluding with a summary of the study's primary findings and contributions.

2. Literature Review

2.1. A Review of Predicting the Stock Price with LSTM

The advantages of LSTM networks for forecasting financial time series data have been extensively documented in academic research. Chen et al. (2015) applied LSTM to predict stock returns in the Chinese market. They segmented historical data into 30-day sequences, each including ten learning features, and found that LSTM significantly improved forecasting accuracy from 14.3% (baseline) to 27.2%, clearly outperforming random prediction models. Similarly, Fischer and Krauss (2018) assessed LSTM's performance in classifying directional movements of S&P 500 stocks between 1992 and 2015. They concluded that LSTM significantly surpassed traditional methods such as logistic regression, random forests, and conventional deep neural networks. In a comparative study, Yu and Yan (2020) integrated LSTM with phase-space reconstruction techniques, forecasting prices of multiple indices, including the S&P 500, DJIA, and Nikkei 225. Their results demonstrated the clear superiority of LSTM over other methods like Multilayer Perceptron, Support Vector Regression, and ARIMA, particularly highlighting strong performance with the S&P 500 dataset. In addition, Karmiani et al. (2019) evaluated various predictive algorithms, LSTM, SVM, Backpropagation, and Kalman filters, on stock data from nine companies. Their findings confirmed that LSTM achieved the highest accuracy and lowest variance among all tested methods. Further emphasizing LSTM’s effectiveness, Niu et al. (2020) conducted comparative analyses on daily closing price predictions across indices such as the Hang Seng, S&P 500, FTSE, and Nasdaq between 2010 and 2019. They observed consistently lower root mean square errors (RMSE) for LSTM, particularly noting exceptional performance in predicting Nasdaq index prices. Similarly, Xiao et al. (2022) examined daily stock price forecasts across 50 stocks from 2010 to 2018. Their study reaffirmed LSTM's predictive advantage over ARIMA, attributing its superior performance to the model’s memory capabilities and its ability to capture intricate temporal dependencies. However, they also noted considerable variation in LSTM performance across different stocks, suggesting that forecasting accuracy might depend on stock-specific characteristics. Furthermore, Karaboga et al. (2024) evaluated LSTM and Random Forest (RF) models to predict daily closing prices of Turkcell’s stock, using data from both BIST and NYSE (2010–2023). Their results clearly demonstrated that LSTM achieved better forecasting accuracy than RF, particularly for the NYSE dataset. Finally, Sönmez and Arslan (2024) assessed LSTM's predictive ability for the BIST-100 and Frankfurt Stock Exchange's DAX index, using various volatility indices as input variables. Covering data from January 2012 to June 2024, their study validated LSTM’s strength in capturing long-term temporal relationships and confirmed its strong forecasting performance.

2.2. The Review of ESG Impact on the Stock Performance

There is growing academic interest in how ESG factors influence stock prices, as more investors consider sustainability in their decision-making. Several studies have examined how ESG performance impacts stock returns and firm valuation. For instance, Cek and Eyupoglu (2020) assess the impact of ESG performance on the economic performance of S&P 500 firms using data from 2010 to 2015 and applying structural equation modeling and regression analysis. They find a significant overall relationship between ESG and economic performance, with social and governance factors showing consistent positive effects. Environmental performance, however, does not exhibit a significant impact. Yoon et al. (2018) applied Ohlson's valuation model to 705 Korean firms from 2010 to 2015. They found a positive relationship between corporate social responsibility and share prices, especially in industries with high environmental or social sensitivity. Similarly, Deng and Cheng (2019) analyzed data from Chinese firms between 2015 and 2019 using panel regression. Their results showed that higher ESG ratings were associated with better stock returns. They also noted that this effect was stronger for private companies compared to public ones. Furthermore, Buallay (2019) examined 235 banks from 2007 to 2016 and reported that ESG ratings had a positive impact on firm market value. In the MENA region, Al-Hiyari and Kolsi (2021) conducted a study on 439 companies across 10 countries during 2013–2019. Their findings also showed a positive link between ESG performance and market value. Engelhardt et al. (2021) investigate the relationship between ESG ratings and stock performance during the COVID-19 crisis. Analyzing a sample of 1,452 firms across 16 European countries, they find that companies with high ESG ratings experienced higher abnormal returns and lower stock volatility, suggesting better performance compared to firms with low CSR ratings. Another study by Berg et al. (2022) looked at companies in North America, Europe, and Japan between 2014 and 2020. They found that higher ESG scores were associated with stronger expected returns. Similarly, Lapinskienė et al. (2023) analyzed 500 large U.S. companies and 600 EU firms over the period 2015–2020. Their research highlighted that stock price movements were partly influenced by environmental initiatives, emphasizing the growing importance of the "E" in ESG. Ateş et. al (2022) examine the comparative performance of sustainable-themed funds against traditional funds and indices in Turkey, aiming to determine whether sustainability-focused investments outperform conventional alternatives. Using daily data from 2019 to 2022, they analyze the BIST Sustainable Index (XUSRD) as the benchmark for sustainable funds and the BIST100 Index (XU100) as the benchmark for traditional funds. The Capital Asset Pricing Model (CAPM) is applied to calculate portfolio returns and systematic risks. The results show that sustainable-themed funds demonstrate stronger performance than their traditional counterparts and the broader market indices. More recently, Gül and Altuntaş (2024) investigated 347 companies from both advanced and emerging markets between 2010 and 2022. Their study confirmed a statistically significant positive effect of ESG ratings and return on assets on stock performance, with especially strong results observed in emerging markets.

In contrast to studies demonstrating positive impacts of ESG on financial performance, some researchers report neutral or even negative relationships. Brammer et al. (2006) investigate the relationship between corporate social performance and stock returns in the United Kingdom. Rather than relying on an aggregate measure, they adopt a disaggregated approach, analyzing specific dimensions of social performance, including environmental practices, employment policies, and community engagement. The findings reveal a negative association between composite social performance scores and stock returns. The authors attribute this underperformance primarily to firms' strong environmental initiatives and, to a lesser extent, their community-related activities. Moreover, they report that portfolios composed of the least socially responsible firms yield significant abnormal returns. The authors examine the influence of ESG scores on the risk-taking behavior and firm value of European banks. Their analysis reveals that higher ESG scores are linked to a modest decrease in risk-taking. Also, the authors also find that elevated ESG scores are associated with a decline in bank value. They conclude that ESG initiatives may divert scarce resources away from more value-enhancing investments. Halbritter and Dorfleitner (2015), for instance, examined the U.S. market and found no statistically significant relationship between ESG scores and stock market returns. Their analysis revealed no meaningful differences between high- and low-ESG portfolios. Similarly, La Torre et al. (2020) investigated 46 public companies listed on the Eurostoxx50 from 2010 to 2018 using panel analysis and multiple linear regression. Their findings indicated no significant impact of ESG ratings on corporate financial performance. Luo (2022) studied UK-listed stocks between 2003 and 2020 and presented evidence that firms with lower ESG scores could achieve higher returns. Luo's analysis supports a risk–return trade-off hypothesis, suggesting investors require greater compensation when investing in firms with weaker ESG profiles. Gavrilakis and Floros (2023), analyzing large companies across six European countries over the period 2010–2020, similarly reported that investing in firms with high ESG ratings typically did not lead investors to sacrifice returns. These findings highlight ongoing debates within the literature regarding the precise influence of ESG factors on financial performance.

The abovementioned literature presents conflicting evidence regarding the impact of ESG scores on stock performance. Moreover, most existing research focuses on developed markets, with emerging economies remaining underrepresented. These issues highlight a research gap that this study seeks to address using data from Turkey. Specifically, the study investigates the effect of ESG on BIST-listed stocks, representing an emerging market, through a machine learning approach. The following section provides a detailed description of the dataset and methodology.

3. Data and Methodology

3.1. Data

This study examines the environmental performance of five companies listed on the Borsa Istanbul (BIST) index, using data sourced from MSCI ESG ratings. These firms were selected based on their availability of the MSCI ESG ratings, which have consistently published ESG scores since 2020. The dataset comprises daily stock prices from 1st of January 2020, to 19th of March 2025, offering five ESG ratings to each company. In addition to ESG scores, the study incorporates information on each firm's carbon reduction strategies, obtained from the MSCI ESG Ratings and Climate Research Tool. The selected companies operate across different industries, enabling a cross-sector comparison of environmental performance and its potential influence on stock prices. The use of MSCI data ensures transparency and reliability, as all ESG scores and climate-related disclosures are publicly accessible via msci.com.

Table 1 demonstrates five selected companies listed on the Borsa Istanbul (BIST) index and presents alongside their industries, ESG correlations, and key reasons for their specific ESG risk levels. These companies include Aselsan (ASELS) from defence and aerospace, Ereğli Demir Çelik (EREGL) from steel and metal production, Turkcell (TCELL) from telecommunications, Turkish Airlines (THYAO) from aviation, and Tüpraş (TUPRS) from oil and gas refining. The table also presents each company's ESG correlation levels and the rationale behind these classifications. Companies from heavily polluting industries, such as steel production, aviation, and oil refining, demonstrate a high correlation with ESG issues due to their significant carbon footprints, environmental impacts, and pressures to decarbonize. Turkcell shows a medium-high

ESG correlation, primarily influenced by factors like data privacy, cybersecurity, energy efficiency, and governance practices. In contrast, defence-sector firms like Aselsan typically have medium ESG correlations, mainly influenced by governance risks, ethical concerns, and regulatory scrutiny rather than direct environmental impacts. Thus, analysing this diverse group of companies allows for a detailed exploration of how ESG considerations vary across sectors and how different industries respond to environmental and sustainability pressures.

Table 1. Selected BIST Companies and Their ESG Relevance by Sector

Ticker	Company	Sector	ESG Correlation	Reason
ASELS	Aselsan	Defense & Aerospace	Medium	Defense companies face governance risks, ethical concerns, and regulatory scrutiny but are not always ESG-friendly.
EREGL	Ereğli Demir Çelik	Steel & Metal Production	High	The steel industry is highly polluting and under pressure to shift toward green steel and decarbonization.
TCELL	Turkcell	Telecommunications	Medium	Telecom companies are evaluated on data privacy, cybersecurity, energy efficiency, and governance practices.
THYAO	Turkish Airlines	Aviation	High	Airlines have high carbon footprints, and ESG ratings depend on their sustainability initiatives (e.g., sustainable aviation fuel, carbon offsets).
TUPRS	Tüpraş	Oil & Gas Refining	High	Fossil fuel companies are ESG-sensitive due to emissions, environmental risks, and transition pressure toward cleaner energy sources.

Following the approach of Ruan and Liu (2021), the qualitative MSCI ESG ratings were converted into numerical values to facilitate quantitative analysis. As shown in Table 2, ratings ranging from 'CCC' to 'AAA' were assigned scores from 1 to 7, respectively. This numerical representation allows for consistent integration of ESG data into the forecasting model.

Table 2. MSCI ESG Ratings and Corresponding Scores

ESG Rating	AAA	AA	A	BBB	BB	B	CCC
Assigned ESG Score	7	6	5	4	3	2	1

Similarly, decarbonization efforts were quantified using a scoring framework adapted from Le Guenedal et al. (2025) and In et al. (2019). Table 3 outlines the classification of carbon reduction targets into six levels, with corresponding scores ranging from 0 (no target) to 100 (net-zero target with detailed plans and full disclosures). This scoring system captures the degree of commitment and specificity in a firm’s climate strategy.

Table 3. MSCI Carbon Emission Targets and Assigned Scores

Level	Description	Example	Assigned Score
0	No target	No stated reduction goal	0
1	Vague, unquantified target	“We aim to reduce emissions someday”	20
2	Quantified but not time-bound	“We aim to cut emissions by 30%”	40
3	Medium-term, quantified, no science-based validation	“50% by 2030, but no SBTi alignment”	60
4	Near-term, science-based or SBTi-approved target	“SBTi 1.5°C-aligned by 2030”	80
5	Net-zero, detailed transition plan, transparent disclosures	Net-zero by 2050 + scope 3 + roadmap	100

Figure 1 demonstrates the letter scores for the five selected BIST-listed companies—Aselsan (Asels), Ereğli Demir ve Çelik (Eregl), Turkcell (Tcell), Turkish Airlines (Thyao), and Tüpraş (Tuprs)—over the 2020–2024 period. These scores reflect variations in environmental performance across time and sectors. Table 4 presents the corresponding scalar scores for these letter scores given in Figure 1.

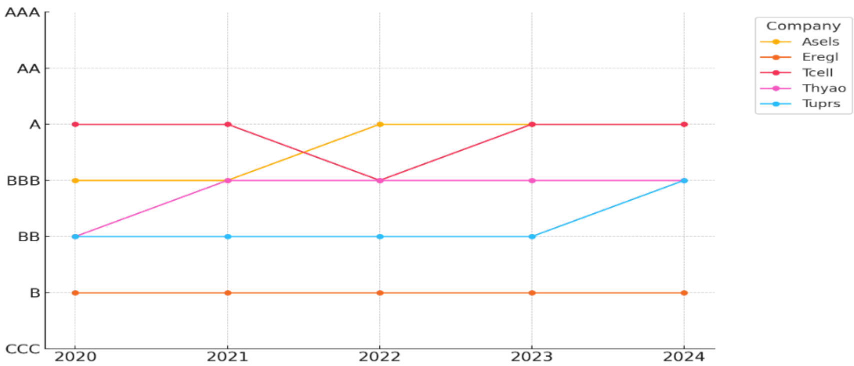

Figure 1. ESG Scores of the Selected Companies 2020-2024

Table 4. Selected Companies ESG Scores

Year	Asels	Eregl	Tcell	Thyao	Tuprs
2020	4	2	5	3	3
2021	4	2	5	4	3
2022	5	2	4	4	3
2023	5	2	5	4	3
2024	5	2	5	4	4

Table 5 summarizes the decarbonization scores assigned to each company based on the most recent available data. The scores reveal notable differences in the ambition and clarity of emissions targets, providing a foundation for evaluating the relationship between decarbonization efforts and stock market performance.

Table 5. Selected Companies Decarbonization Scores

	Asels	Eregl	Tcell	Thyao	Tuprs
Level	4	1	4	3	2
Score	80	20	80	60	40

3.2. Methodology

In this study, an LSTM model for stock price prediction is tested over data set belonging to 5 different BIST 100 companies from various industries. In this case, it will be a parallel of performing three modeling treatments on the same company data for the same period. The application is written using Python.

The first model is simply a baseline that uses only historical stock price data, mimicking a conventional financial forecasting model—one that does not incorporate greenhouse gas emissions or other sustainability-related input. The second model builds on this baseline by including ESG scores, allowing us to measure their impact on the predictive accuracy of the model. The third model includes corporate decarbonization targets as additional inputs, allowing you to see how climate commitments impact price predictions.

The methodology follows a structured methodology consisting of five main steps to evaluate the performance of an LSTM model for stock price prediction. The methodology involves data processing, model construction, and performance evaluation using data from five BIST 100 companies across various industries.

Step 1: Editing the Data

The first step involves collecting and reviewing financial and environmental data. Five selected BIST 100 companies' historical stock prices and ESG scores, and corporate decarbonization targets are obtained. The datasets are synchronized and standardized to be uniform, and timestamps are aligned among all features to enable synchronized input to the LSTM. This step also standardizes the datasets from different sources and makes them structurally and in terms of content uniform.

Step 2: Preprocessing of the Data

All input features are normalized while preprocessing by utilizing the MinMaxScaler from the scikit-learn library. The stock prices and other features are normalized between 0 and 1 and are made ready to train the model. ESG scores are normalized between 1 and 7 to prevent the model from becoming idle due to zero inputs. Normalization supports faster and improved learning and convergence of the model. The inputs are also reshaped to maintain the dimensions as per the requirements of recurrent neural networks.

Step 3: Training and Test Data Sets

To ensure robust generalization and minimize the risk of overfitting, the dataset is partitioned chronologically into training, validation, and testing subsets. This temporal ordering preserves the natural autocorrelation structure of time-series data and prevents data leakage across modeling stages. At the firm level, an 80–20 chronological split is implemented: the earliest 80% of observations form the model development window, while the most recent 20% serve as an out-of-sample test set. Within the development window, the final 10% is reserved as a validation set for hyperparameter tuning, following an expanding window procedure. This results in an effective 72/8/20 split for training, validation, and testing, respectively.

Step 4: The LSTM Algorithm

The LSTM model was developed using TensorFlow's Keras Sequential API, with Dense layers added to support output processing. Several versions of the model were tested to evaluate performance under different input conditions. The first was a baseline model that relied solely on historical closing price data. Another version incorporated five ESG score inputs to capture sustainability-related factors. Finally, a third model included decarbonization target inputs to assess the impact of climate-focused goals on performance.

The model architecture includes special LSTM units that regulate data flow through three primary gates: the input gate, the forget gate, and the output gate (Oancea and Simionescu, 2024). These gates utilize sigmoid activation functions to manage memory updates and retain long-term patterns. The input gate is responsible for determining how much of the new input should be stored in the cell state. The forget gate decides which parts of the previous cell state should be removed. The output gate controls the amount of information from the cell state that will be passed to the next hidden state. The cell structure is presented in Figure 1.

Mathematically, the gates operate as follows:

$$\textit{Input gate: } i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad (1)$$

$$\textit{Forget gate: } f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \quad (2)$$

$$\textit{Output gate: } o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \quad (3)$$

A sequence length of 64 was selected after testing various lengths (10, 32, 64, 100, 134), as it provided the most reliable performance. The Adam optimizer was employed for training, offering adaptive learning capabilities suitable for time-series modeling. The model architecture is presented in Figures 2 and 3.

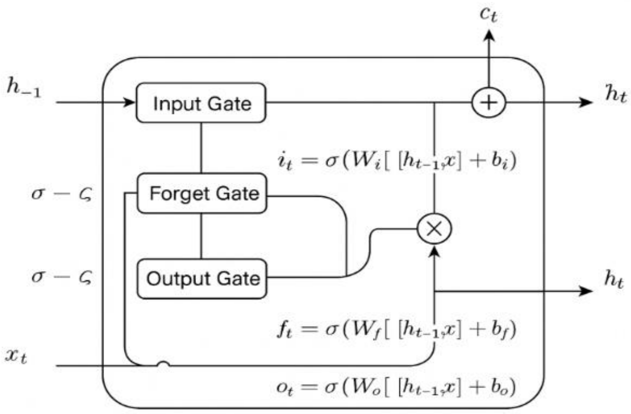

Figure 2. A LSTM Cell

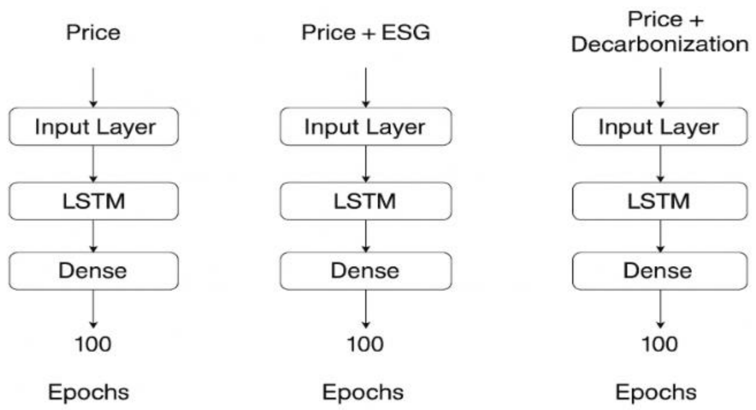

Figure 3. The Model Architecture

Hyperparameter tuning followed a structured, coarse-to-fine search protocol, employing validation splits and an expanding window evaluation approach to maintain temporal integrity. The optimal number of LSTM units was established at 50, providing adequate representational capacity without over-parameterization issues encountered with higher unit counts. Batch size was set to 32, optimizing gradient stability and efficiency, as smaller batches increased gradient noise, and larger batches slightly degraded validation accuracy. The Adam optimizer was chosen due to its effective adaptive learning rate for non-stationary data sequences, offering faster and more stable convergence compared to alternative methods. An initial learning rate of 0.001, determined via grid search $10^{-2}, 10^{-3}, 10^{-4}$ ensured smooth loss progression without excessive oscillation. Regularization involved applying a dropout rate of 0.2 to LSTM outputs before the Dense layers, effectively mitigating overfitting without significantly compromising training performance. Higher dropout rates (≥0.3) impaired learning, while lower rates (<0.2) insufficiently controlled variance.

Step 5: Performing the Estimation Process and Measuring Its Accuracy

The estimation process involved training each version of the LSTM model for 100 epochs, which was identified as the optimal count, balancing training time and performance. During this process, the model made predictions for the next five trading days using the preceding 64 days as input. Performance was measured using error analysis, focusing on how the inclusion of additional features (ESG scores and decarbonization targets) affected prediction accuracy. After training, the normalized outputs were converted back to actual stock prices using inverse transformation, enabling the interpretability of the results. Through this iterative learning and evaluation, the model refined its internal parameters to improve predictive performance over time.

3.3. Error Measurements Metrics

Three widely used error measurement metrics, namely Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), are used to evaluate the predictive performance of the LSTM models (Botunac et al., 2024). These metrics provide complementary insights into model accuracy. MAE measures the average magnitude of the prediction errors without considering their direction, offering a straightforward interpretation of the model's accuracy. MSE, by squaring the errors, penalizes larger deviations more heavily, making it sensitive to outliers. RMSE, as the square root of MSE, retains the same unit as the target variable and offers a balanced view by combining the benefits of both MAE and MSE. Together, these metrics enable a comprehensive assessment of the model's forecasting capability. The metrics are given as:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{4}$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{5}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

In these formulas, y_i represents the actual value, $\hat{y}_i$ is the predicted value, and n is the total number of predictions. These metrics together provide a comprehensive view of model accuracy and help identify the most effective input combinations.

4. Results and Discussion

This part explores the predictive capability of the LSTM model in forecasting stock prices under three different data configurations: (1) using historical price data alone, (2) integrating historical prices with ESG scores, and (3) combining historical prices with companies' decarbonization targets. The goal is to assess whether the inclusion of sustainability-related information enhances the model's forecasting performance, and if so, which stocks are most sensitive to these additional data sources. In addition to time-series prediction plots, the study includes histogram and Kernel Density Estimation (KDE) plots for each stock across the three cases. These plots provide a visual comparison between the distribution of actual prices and the distribution of LSTM-predicted prices, highlighting how well the model captures the statistical structure and variance in stock price behavior. Also, MAE, MSE, and RMSE error measurements are provided for all cases.

In the first case, the LSTM model was trained solely on historical price data. The results serve as a benchmark for evaluating the effects of incorporating ESG and decarbonization variables. In Figure 4, visually, the LSTM model exhibits strong predictive performance, closely following the trends and short-term fluctuations of the actual price series. The results are also supported by the histograms and KDE in Figure 5, which indicate a reasonably close match between actual and predicted price distributions.

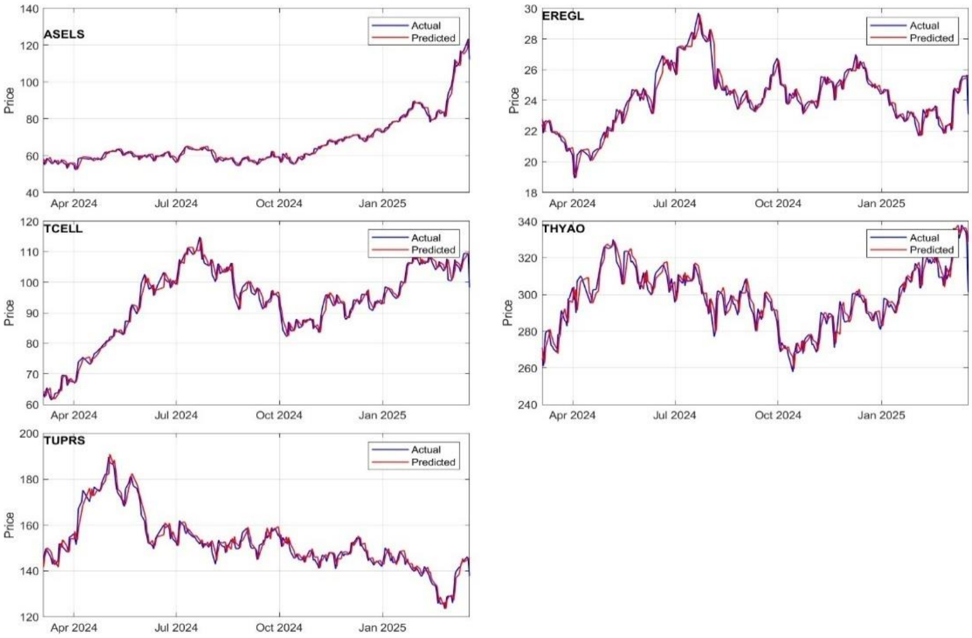

Figure 4. Actual Prices Versus Predicted Prices – First Case: Price Only

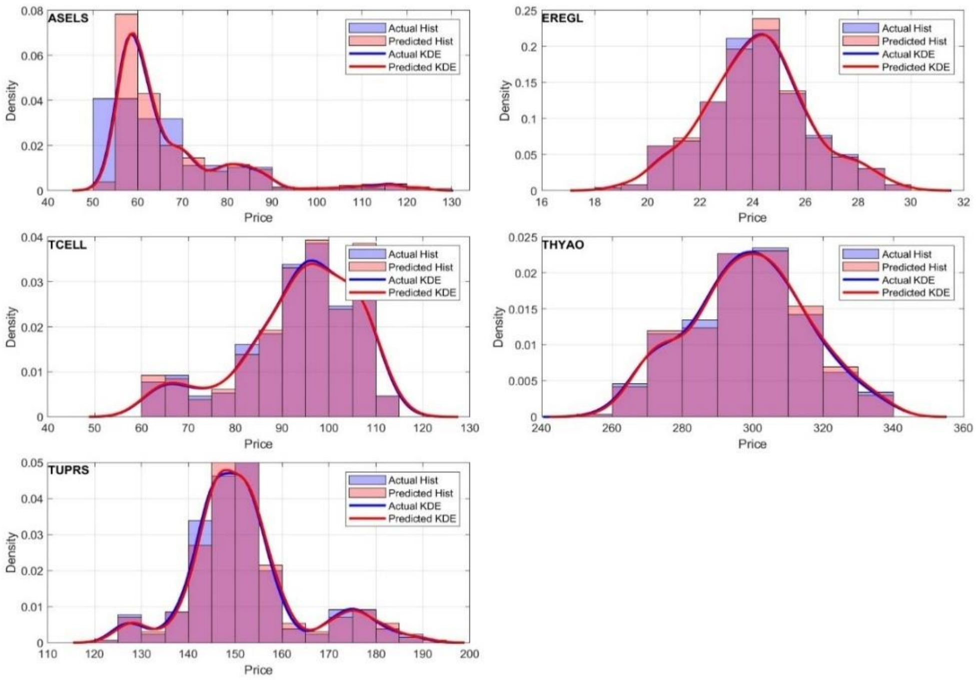

Figure 5. Histograms and KDEs of Actual Prices Versus Predicted Prices – First Case: Price Only

In Table 6, the results indicate that while the model generally tracks the stock price patterns closely, its accuracy varies significantly across companies. EREGL exhibits the lowest RMSE at 0.5177, indicating a relatively stable and predictable price trajectory, which the LSTM model captures effectively. In contrast, THYAO shows the highest RMSE at 5.7448.

Table 6. Error Metrics - First Case: Price

Stock	MAE	MSE	RMSE
ASELS	1.2592	3.1893	1.7859
EREGL	0.37863	0.26797	0.51766
TCELL	1.5547	4.3256	2.0798
THYAO	4.5348	33.003	5.7448
TUPRS	2.1846	7.3023	2.7023

In the second case, ESG scores are added as an additional feature alongside historical price. Visually, in Figure 6, it exhibits strong predictive performance, closely following the trends and short-term fluctuations of the actual price series. The inclusion of ESG data results in modest but consistent improvements in model performance across all five companies. The RMSE dropped slightly for every stock, suggesting that ESG data may carry supplementary explanatory power beyond price history.

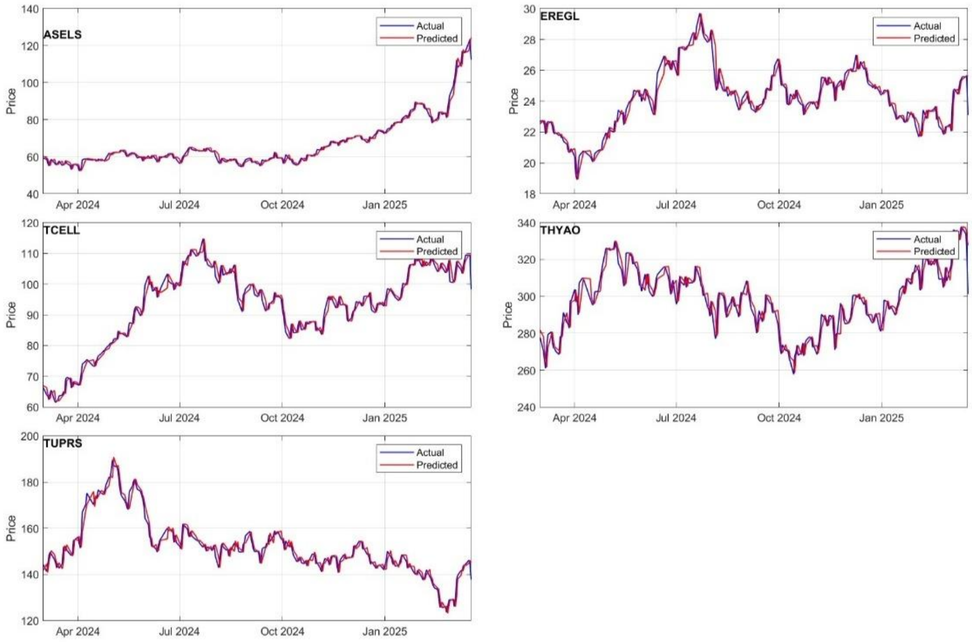

Figure 6. Actual Prices Versus Predicted Prices – Second Case: Price + ESG

In Figure 7, with the inclusion of ESG scores, the predicted histograms show improved alignment with the actual price distributions for most stocks. For instance, ASELS now exhibits a KDE curve that more accurately captures the steep peak in the lower price range. This change supports the idea that ESG scores provide additional explanatory power, helping the model better understand the concentration of values around certain price levels. Similarly, THYAO's predicted distribution more closely resembles the actual one, particularly in terms of symmetry and spread. The tail behavior for TUPRS is also better captured in this configuration, reflecting improved prediction of rare or less frequent price levels.

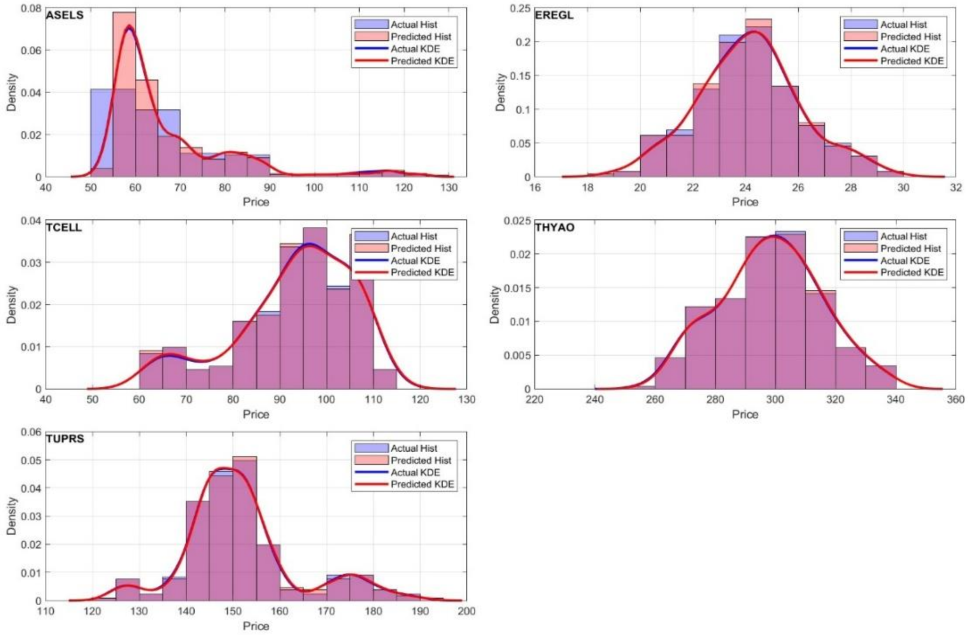

Figure 7. Histograms and KDEs of Actual Prices Versus Predicted Prices – Second Case: Price + ESG

As seen from Table 6 and Table 7, THYAO demonstrates a substantial improvement with a reduction in RMSE from 5.7448 to 5.5980. This is significant, as THYAO operates in the aviation sector—an industry that is highly exposed to ESG-related risks, including carbon emissions, fuel efficiency, and regulatory pressures. The improvement suggests that market participants may be incorporating ESG information into their pricing decisions for such firms, and the LSTM model benefits from having this context. The other companies show smaller but still positive gains. Contrary to the expectations that EREGL and TUPRS, both in carbon-intensive sectors, should be affected by the ESG score more, they did not. For instance, ASELS sees a minor drop in RMSE to 1.7789, while TUPRS decreases to 2.6414. The consistency of these improvements across all stocks suggests that ESG scores provide valuable supplementary information that captures qualitative or intangible aspects of firm performance not evident in price data alone. Although the magnitude of performance enhancement is modest, it is statistically meaningful given the model's complexity and the noise inherent in financial markets.

Table 7. Error Metrics - Second Case: Price + ESG

Stock	MAE	MSE	RMSE
ASELS	1.2683	3.1644	1.7789
EREGL	0.37166	0.26178	0.51165
TCELL	1.5336	4.1817	2.0449
THYAO	4.3652	31.337	5.598
TUPRS	2.133	6.9771	2.6414

In the third scenario, decarbonization targets are used instead of ESG scores, and actual versus predictive stock prices are presented in Figure 8. The model again shows high accuracy, closely following the actual price's trends and movements, similar to Figure 6. Importantly, leveraging decarbonization data provided small but reliable performance gains for all five companies. While the visual difference between the predicted prices in Figure 6 and Figure 8 is subtle, Table 8 quantifies the performance improvement.

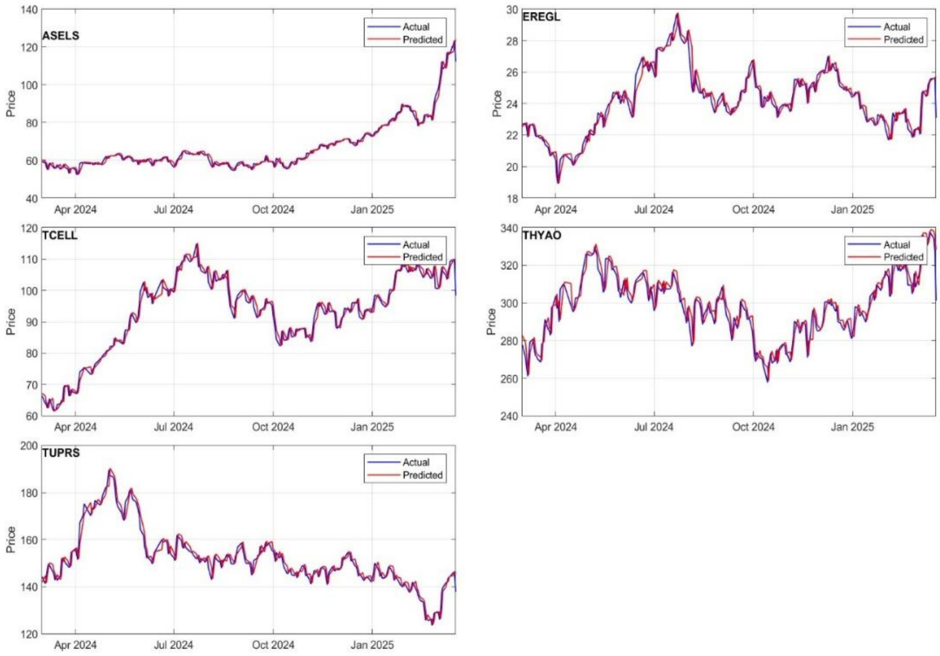

Figure 8. Actual Prices Versus Predicted Prices – Third Case: Price + Decarbonization

In Figure 9, where decarbonization targets are included, the histogram plots reveal more varied results across stocks. For some firms—particularly THYAO and TUPRS—the predicted distributions improve further, closely aligning with the actual KDE curves in both the center and the tails. This suggests that carbon-related disclosures enhance the model's ability to capture price behavior in industries more exposed to environmental regulations and carbon pricing. In contrast, the predictions for ASELS show a slight mismatch. The predicted KDE curve becomes wider and less sharp, indicating that decarbonization data may add noise rather than useful signals for this stock, likely due to its lower sensitivity to carbon-related factors. TCELL presents another interesting case. Although the predicted and actual distributions generally align well, the inclusion of decarbonization targets introduces mild overfitting in the central region, where the model produces an overly smooth curve that misses the slightly multimodal shape of the actual data. This may suggest that for telecom companies like TCELL, ESG factors are more informative for stock prediction than specific carbon metrics.

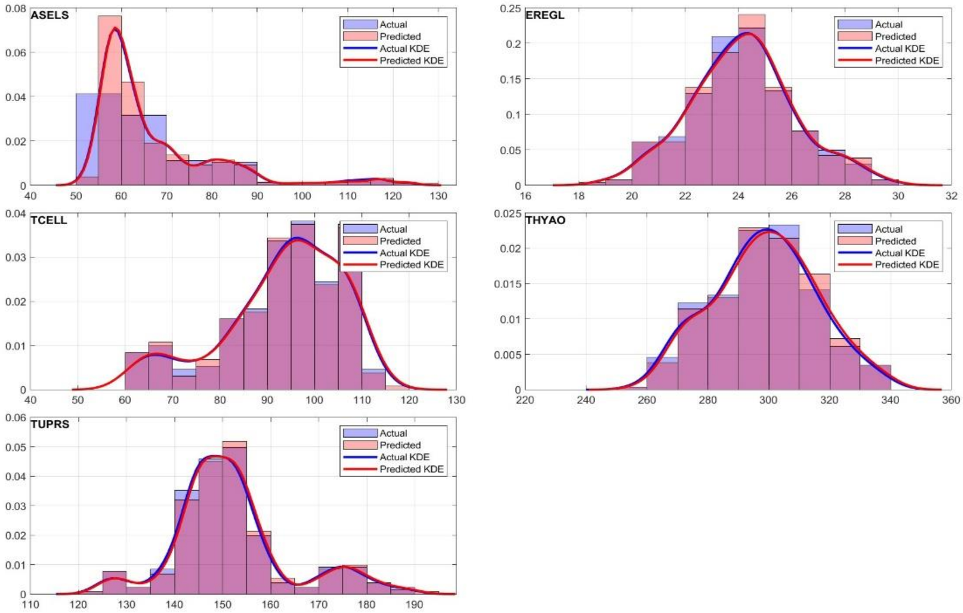

Figure 9. Histograms and KDEs of Actual Prices Versus Predicted Prices – Third Case: Price + Decarbonization

Table 8 demonstrates the performance results of the third case. Based on the results in Table 8, THYAO continues to show strong sensitivity to sustainability-related data, with its RMSE dropping from 5.7448 in the baseline model to 5.5199 in the model that includes decarbonization targets. This larger improvement, compared to the ESG-enhanced model, likely reflects the aviation industry's heightened exposure to carbon-related risks and investor focus on emissions. Similarly, TUPRS sees a meaningful improvement, with RMSE falling from 2.7023 to 2.5782. Given its likely position in the energy or petrochemical sector, TUPRS is naturally impacted by carbon policies, which can shape both regulatory obligations and investment decisions. In contrast, EREGL and TCELL show only minor improvements, with RMSE reductions of around 0.006 and 0.033, respectively—nearly identical to the gains observed with ESG data alone. This suggests that decarbonization targets do not add much additional predictive value beyond what is already captured by ESG metrics for these stocks. ASELS, however, stands out as an exception. Its RMSE slightly increases from 1.7859 to 1.8377 after adding decarbonization data, implying a misalignment between these variables and the drivers of its stock performance. This may be due to ASELS's industry—possibly defense or electronics—where carbon-related issues are less central, making such data less relevant and potentially introducing noise into the model.

Table 8. Error Metrics - Third Case: Price + Decarbonization

Stock	MAE	MSE	RMSE
ASELS	1.2823	3.3772	1.8377
EREGL	0.3706	0.2617	0.51157
TCELL	1.5402	4.1908	2.0472
THYAO	4.229	30.469	5.5199
TUPRS	2.0673	6.647	2.5782

Overall, companies operating in sectors with high emissions exposure—THYAO and TUPRS—showed the strongest improvements in prediction accuracy when these targets were added. For example, THYAO's RMSE dropped significantly, suggesting that investors actively respond to decarbonization plans in high-impact industries. In aviation, where emissions reduction is difficult and regulation is tightening (e.g., EU ETS, CORSIA), carbon targets may be a proxy for operational viability, investment risk, or access to green capital. Likewise, TUPRS, operating in oil refining—a fossil-fuel-intensive industry—benefited significantly from decarbonization data. The LSTM model's improved distributional fit in this case suggests it could better approximate price behavior by integrating transition-relevant features like emission reduction timelines, capital expenditures on cleaner tech, and strategic alignment with low-carbon pathways. By contrast, ASELS exhibited a slight decline in performance when decarbonization targets were added. This likely stems from the limited role that carbon emissions play in the defense industry's valuation or regulatory risk profile. Including such features in the model may have added noise without improving explanatory power. TCELL and EREGL both showed similar, marginal gains with decarbonization data as they did with ESG scores. This indicates that while transition data may not drastically shift their price behavior, it still holds some predictive value, likely reflecting broader institutional investor sentiment.

The empirical results of this study align in part with the broader academic literature on the relationship between ESG factors and stock performance, though they also raise important differences. A substantial body of research, including studies by Yoon et al. (2018), Deng and Cheng (2019), and Berg et al. (2022), has demonstrated a positive association between strong ESG performance and improved stock valuation or returns, particularly in environmentally or socially sensitive sectors. This aligns with the modest yet consistent improvements observed in the results when ESG and decarbonization data were integrated into predictive models. Stocks such as TUPRS and THYAO, which showed noticeable declines in RMSE with the inclusion of these factors, may reflect the dynamics identified in prior studies, where firms exposed to environmental risks respond more significantly to ESG-related inputs. In addition, these results reflect the conclusions of Lapinskienė et al. (2023) and Gül and Altuntaş (2024), who emphasize the importance of environmental metrics and their heightened effects in emerging markets. The companies in this study operate in an emerging country, further supporting this interpretation.

However, the improvements in forecasting accuracy are generally small, and in some cases such as EREGL almost negligible. This brings into question the overall relevance of ESG information across all sectors and companies. Similar concerns are raised in studies by Halbritter and Dorfleitner (2015), La Torre et al. (2020), and Luo (2022), who argue that ESG factors may not always affect financial performance or that their influence depends on the specific context, such as industry type, geographic location, or investor preferences. The findings of this study point to the same idea: while ESG and decarbonization data can improve model accuracy in certain cases, their overall impact is limited and not consistent across all firms. This suggests a need for more detailed analyses that consider how relevant ESG factors are for different sectors or companies. It also points to the importance of improving methods used to capture the complex relationship between sustainability data and financial outcomes. Additionally, the inconsistency may also stem from discrepancies among ESG scores from different providers (e.g., MSCI, LSEG, Sustainalytics). As Dorfleitner et al. (2015) note, these scores often conflict and may not accurately reflect a company's true sustainability practices, increasing the risk of misinterpretation. Overall, the study shows that ESG data can be useful in stock prediction, but its value is uneven and should be used carefully in financial modeling.

5. Conclusion

This study explored the effectiveness of an LSTM-based model in predicting stock prices using a combination of historical financial data and sustainability metrics, specifically ESG scores and corporate decarbonization targets. Using data from five BIST 100 companies between 1 January 2020 and 19 March 2025, the study examined how the inclusion of these non-financial variables affected predictive performance across different sectors.

The results show that the integration of sustainability data produced mixed outcomes. In high-emission sectors such as aviation (THYAO), oil refining (TUPRS), and steel production (EREGL), the inclusion of ESG and decarbonization data led to improvements in model accuracy, as measured by MAE, MSE, and RMSE. THYAO exhibited the most significant gains, particularly with decarbonization targets—likely due to the strong regulatory and investor focus on climate performance in the airline industry. TUPRS also saw notable improvements, aligning with the oil sector's exposure to energy transition risks. Interestingly, the results for EREGL were more modest than expected. Given the steel industry's substantial carbon footprint and increasing regulatory and market pressure to adopt low-emission practices, a higher sensitivity to sustainability metrics was anticipated. In contrast, companies in sectors less directly impacted by environmental pressures responded differently. TCELL, representing the telecom industry, showed moderate improvements, particularly with ESG inputs, but limited sensitivity to decarbonization data. For ASELS, a defense and aerospace firm, ESG scores offered only marginal predictive value, and decarbonization inputs slightly degraded model performance—reflecting the sector's misalignment with conventional sustainability frameworks.

Overall, while the improvements are not dramatic, the findings suggest that sustainability metrics can enhance LSTM model performance when they are materially relevant to a company's core operations. However, their predictive value is not universal. The study highlights the importance of aligning input features with sector-specific realities. While LSTM proved effective at modeling complex, time-dependent relationships, the results underline that thoughtful feature selection—based on contextual relevance—is key to achieving meaningful gains in predictive accuracy.

The present study's findings are shaped by the specific ESG measurement framework used; as different providers often produce conflicting ratings, results may vary by data source. To improve external validity, future work should incorporate multiple ESG providers to address issues of measurement error and timing. Additionally, future studies should consider including a larger and more diverse set of companies, both in terms of geography and industry, to make the findings more broadly applicable. Exploring other deep learning models, such as GRUs or Transformers, could also help identify which approaches work best for stock prediction. Finally, combining ESG data with macroeconomic indicators or market sentiment could provide a fuller picture of investor behavior and improve the practical value of sustainability-focused forecasting. Furthermore, policymakers should encourage companies to share more detailed ESG and decarbonization information, as this can help investors and analysts make better predictions and decisions. Standardizing ESG data across industries would make it easier to compare companies and assess their long-term value.

In addition, future research should investigate the temporal dynamics of ESG and decarbonization data, examining how their predictive value evolves alongside regulatory changes, market shifts, or global events such as the COVID-19 pandemic. Cross-market comparisons between developed and emerging economies could provide deeper insight into how sustainability factors interact with varying institutional environments. Policymakers, meanwhile, should prioritize harmonizing ESG reporting frameworks across jurisdictions to reduce data fragmentation and enable more robust comparative analyses. Encouraging companies to disclose transparent, verifiable, and sector-specific decarbonization strategies would further enhance both academic inquiry and practical forecasting. Finally, integrating explainable AI techniques into sustainability-focused prediction models could improve interpretability, fostering greater trust among investors, regulators, and corporate stakeholders.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher’s Conflict of Interest
There are no potential conflicts of interest in this study.

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