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ARAŞTIRMA MAKALESİ / RESEARCH ARTICLE

GREEN BOND INDEX PRICE FORECASTING: COMPARATIVE ANALYSIS OF MACHINE LEARNING MODELS

YEŞİL TAHVİL FİYAT TAHMİNİ: MAKİNE ÖĞRENMESİ MODELLERİNİN KARŞILAŞTIRMALI ANALİZİ

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Abstract

The aim of this study is to compare the performance of different models using machine learning algorithms to predict the price of the green bond index in Japan. In the study, 693-day dataset collected between 06.05.2021-02.05.2024 was used. Nikkei225, USD/JPY and crude oil prices were determined as input data. 80% of the data was reserved for training and 20% for testing. RF, MLP, GBR, XGBoost, LSTM, SVR, Catboost and Linear Regression methods were used as prediction models. Performance evaluations were made on metrics such as MSE, RMSE, MAE, MAPE and R2. The GBR model showed the best performance in the training set, while XGBoost and RF models produced more successful predictions in the test set. The contribution of this study to the literature is to demonstrate the usability of artificial intelligence-based prediction models in sustainable finance and green bond markets. The results obtained serve as a guide for investors and analysts and offer practical solutions to increase interest in green projects.

Keywords: Green bonds**,** Time series analysis**,** Financial Forecasting, Machine Learning, Decision Support.
Jel Codes: C53, D53, G17.

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Öz

Bu çalışmanın amacı, Japonya'daki yeşil tahvil endeksinin fiyatını tahmin etmek için makine öğrenmesi algoritmalarını kullanarak farklı modellerin performansını karşılaştırmaktır. Çalışmada, 06.05.2021-02.05.2024 tarihleri arasında toplanan 693 günlük veri seti kullanılmıştır. Giriş verileri olarak Nikkei225, USD/JPY ve ham petrol fiyatları belirlenmiştir. Verinin %80'i eğitim, %20'si test için ayrılmıştır. Tahmin modelleri olarak RF, MLP, GBR, XGBoost, LSTM, SVR, Catboost ve Lineer Regresyon yöntemleri kullanılmıştır. Performans değerlendirmeleri MSE, RMSE, MAE, MAPE ve R2 gibi metrikler üzerinden yapılmıştır. Eğitim setinde en iyi performansı GBR modeli göstermiş, test setinde ise XGBoost ve RF modelleri daha başarılı tahminler üretmiştir. Bu çalışmanın literatüre katkısı, sürdürülebilir finansman ve yeşil tahvil piyasasında yapay zeka tabanlı tahmin modellerinin kullanılabilirliğini göstermesidir. Elde edilen sonuçlar, yatırımcılar ve analistler için rehber niteliğinde olup, yeşil projelere olan ilgiyi artırmaya yönelik pratik çözümler sunmaktadır.

Anahtar Kelimeler: Yeşil tahviller, Zaman serisi analizi, Finansal Tahminleme, Makine Öğrenmesi, Karar Destek.

Jel Kodları: C53, D53, G17.

1. Introduction

Global warming and other environmental problems cause the earth's finite natural resources to be rapidly depleted, making it less likely that the planet will ever be habitable. Factors like population growth, increased energy demand, and climate changes enhance the importance of green projects such as renewable energy investments. The concept of green transformation has started to be adopted in a wide range of areas, from the economy to social life, consumption habits to new technologies, and production methods to investment instruments; however, sustainability-focused practices require financing. Green bonds are significant investment instruments that address this need by providing financial support for green transformation projects. The income generated from these bonds, which are debt instruments, finances environmental projects such as combating the climate crisis and renewable energy (ICMA, 2021). Green bonds aim to contribute to economic development while protecting the environment, increasing their popularity. First issued by the European Investment Bank in 2007, green bonds have been issued in Turkey since 2016.

It would be appropriate to briefly examine the status of green bonds globally. According to the latest quarterly market report of the Climate Bonds Initiative published in June 2024, green bonds are on track to reach $1 trillion in 2024. In the first quarter (Q1) of 2024, $272.7 billion worth of aligned green, social, sustainability, sustainability-linked and transition (GSS+) bond volume was added. This amount was 15% higher than the $237.2 billion in the first quarter of 2023 and 41% higher than the $193 billion in the fourth quarter of 2023. Green bonds were the largest contributor, raising $195.9 billion in the opening months of the year, setting a new quarterly record. Lifetime green bond volume has exceeded the $3 trillion mark since the market debut in 2006, contributing to a cumulative GSS+ bond volume of $4.7 trillion. Green bonds continue to be the largest contributor, accounting for 72% of the total, with total conforming issuance volume reaching US$195.9 billion, up 25% compared to Q1 2023 and 43% compared to Q4 2023 (Table 1). As seen in Table 2, Europe leads the green bond market with a share of 58%. Compliant volume from the region reached USD

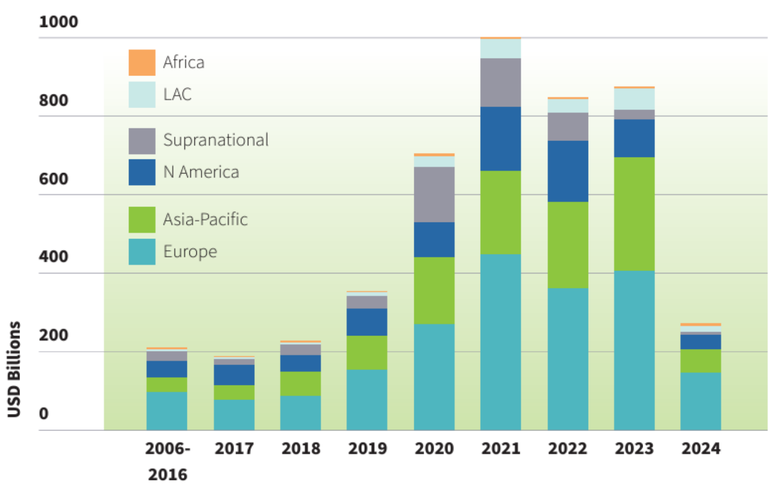
113.2 billion with pricing from 246 issuers in Q1. Asia-Pacific followed with USD 40 billion and North America with USD 30.1 billion (Climate Bonds Initiative Report, 2024a).

Table 1: Aligned GSS+ debt

	Q1 2024		Cumulative since 2006	
	USDbn	Contribution	USDbn	Contribution
Green	195.9	72%	3003	64%
Social	42.3	16%	875	19%
Sustainability	31.4	11%	780	16%
Sustainability-linked bonds	3.1	1%	51	1%
Total	272.7	100	4709	100%

Source: Climate Bonds Initiative, 2024a

Table 2: Aligned Q1 Volume by World Region



Source: Climate Bonds Initiative, 2024a

It is possible to observe that green bonds have garnered significant interest as an important instrument for financing sustainable projects. As noted, green transformation projects, such as renewable energy, are crucial to preserving the right of future generations to utilize existing resources. Countries, institutions, and organizations have set sustainability goals and are striving to achieve them. For instance, according to data published on the website of the Ministry of Energy and Natural Resources, as of February 2024, the proportion of renewable energy (solar energy) in electricity generation is 51.03%.For instance, data from the Ministry of Energy and Natural Resources indicate that, as of

February 2024, the proportion of renewable energy (solar energy) in electricity generation is 51.03%. This means that half of the natural resources used for energy production are preserved; however, such practices entail high initial costs and performance risks. Green bonds offer an alternative to address this challenge and have the potential to be a sustainable investment tool for countries, institutions, and organizations sensitive to environmental issues (Güneş, 2023).

The revenue from brown bonds could similarly finance such projects, leading to the question of why green bonds should be preferred. The answer can be found in Flammer's 2022 research. Companies demonstrate their environmental sensitivity and commitment reliably through green bonds. In return for this commitment, companies make significant environmental improvements, such as reducing CO2 emissions. Thus, these companies achieve high environmental ratings and become attractive to green investors who value sustainability, social responsibility principles, and environmentally friendly, long-term investments in their portfolios. Naturally, it is also crucial for enable investors to comprehend the market's risks and dynamics regarding green bonds.

This study focuses on the research question: Is it possible to contribute to the confidence of investors and companies in green financial instruments? The data presented regarding the future trends of the green bond market is thought to increase the tendency to invest in these bonds and, consequently, in green projects. Thus, the purpose of this research is to use machine learning algorithms to anticipate the green bond index.

The ability to make fast and reliable predictions in variable market conditions is significant. Machine learning models are algorithms that can predict future movements by learning from past data. They have the ability to generalize and detect relationships and trends with high accuracy that people or traditional analysis methods may not notice. Additionally, they can extract patterns from complex datasets and generalize. Therefore, these algorithms may be more suitable for analyzing financial data with a dynamic, noisy, and unstable structure. They help make earlier and more accurate decisions regarding investment opportunities and risks by automating repetitive and time-consuming tasks, conducting analyses quickly, and increasing prediction precision (Wang et al., 2022; Wasserbacher & Spindler, 2022).

Studies on the price prediction of green bonds and the use of AI-based algorithms in this field are relatively limited. However, researchers such as Çetin (2022), Wasserbacher & Spindler (2022), Kocaarslan & Soytaş (2023), and Kocaarslan & Mushtaq (2024) have obtained guiding and good results in predicting green bond yields or indices with artificial intelligence.

Japan is a major global player in environmental sustainability and green energy investments. The country is known for its investments in energy efficiency and renewable energy sources. Therefore, the green bond market in Japan is an important example reflecting global green investment trends. The "Nikko AM Global Green Bond Fund" index has reliable and up-to-date data representing the outcomes of the green bond market in Japan. This index is widely followed by investors and analysts and can be easily accessed through financial data sources. Analyses using reliable data sources increase the accuracy and reliability of the results of the study. Japan is one of the largest economies in the world and its financial markets are of great importance to global investors. The economic dynamics and general condition of the financial markets in Japan are among the important factors affecting green bond investments. Therefore, the use of the green bond index in Japan contributes to the general results of our study. Japan is in a leading position among the countries issuing green bonds. The size and impact of the green bond market in the country was an important factor in the selection of this index. The green bond market in Japan plays an important role in achieving global sustainability goals and therefore, it is the main focus of our study. Previous studies on the green bond market in Japan have widely used such indices to analyze this market. Adopting an approach consistent with the literature increases the scientific validity and acceptability of our study. In conclusion, the reasons for choosing the "Nikko AM Global Green Bond Fund" index include Japan's green investment potential, data accessibility and reliability, economic dynamics, the size and impact of the green bond market, and an approach consistent with the literature. For these reasons, the use of the green bond index in Japan plays an important role in achieving the purpose of our study.

In this study, the green bond index was predicted using machine learning algorithms. Many traditional machine learning algorithms exist. A comparative analysis was conducted to see which of these perform better in predicting the green bond index. The findings are expected to contribute to researchers who want to create new models using machine learning and to the developing green bond literature. The study conducted a price prediction of the green bond index operating in Japan. The input variables were inspired by the literature and included alternative investment options such as Nikkei225, USD/JPY, and crude oil prices. The study was conducted using 693 days of data from 06.05.2021 to 02.05.2024. 80% was used for training and 20% for testing. The machine learning algorithms selected for the comparative analysis were RF, MLP, GBR, XGBoost, LSTM, SVR, Catboost, and Linear Regression. Performance metrics included MSE, RMSE, MAE, MAPE, and R2.

Our study is organized as follows, with the goal of making a substantial contribution to the body of knowledge on investing guidelines and the green bond market. The literature review is covered in the second section, and the research methodology is covered in the third. The fourth and fifth chapters, respectively, contain the study's conclusions, suggestions, and findings.

2. Literature Review

Academic interest in green bonds, which have the potential to increase investment in environmentally sensitive projects (Lukšić et al., 2022), is steadily rising; however, green bonds remain a relatively new research area. Relevant studies primarily focus on the importance (Kurtoğlu & Çakan, 2022), mechanisms (Zhou & Cui, 2019; Turan, 2022), economic and environmental impacts (Bachelet et al., 2019; Turguttopbaş, 2020; Flammer, 2021; Yağcılar & Yılmaz, 2022; Dumlu & Keleş, 2023), comparisons with traditional bonds (Hachenberg & Schiereck, 2018; Zerbib, 2019), and causality connections. Most studies in the literature employ statistical and econometric analyses, while those using machine learning models for green bond index prediction are limited.

Piñeiro-Chousa et al. (2021) analyzed the impact of investor sentiment on the green bond market using sentiment and panel data analyses. The study found that tweets positively affected green bond returns and identified a negative relationship among the S&P Index, the GSCI Natural Gas Index, and green bond indices.

Çetin (2022) aimed to determine the corporate green bond index value and its predictor using MLF-ANN. The study concluded that the designed model closely aligned the real values of the S&P Green Bond Index.

Chatziantoniou et al. (2022) examined the continuous integration and return transfer among four well-known environmental finance indexes: Dow Jones World Sustainability Index, S&P Green Bond Index, MSCI Global Environment, and S&P Global Clean Energy. The study used a novel quantitative frequency connection approach and found that the S&P Green Bond Index and S&P Global Clean Energy were net receivers of short and long-term shocks.

Wang, Tang, and Guo (2022) presented a hybrid model that forecasts the Chinese green bond market by integrating CEEMDAN and LSTM. The model achieved an MSE value of 0.267635, indicating a prediction accuracy of 73.24%. Predictors included closing price, crude oil market indices, opening price, green stock market indices, trading volume, trading volume turnover, and daily return rate. The most effective predictors were crude oil and green stock market indices.

Kocaarslan and Soytaş (2023) investigated the effect of significant markets, taking into account economic risk variables, on the performance of US municipal green bonds. The study used RF, XGBoost, CatBoost, and LightGBM methods, finding that traditional bond market performance boosted municipal green bond performance pre-COVID-19, still during the COVID-19 crisis, the stock and energy commodities markets had a greater influence.

Adekoya et al. (2023) predicted green bond returns using FQGLS and non-quantitative causality predictors, concluding that speculative factors negatively impacted predictions and commodity and financial asset prices had complex effects.

Güneş (2023) attempted to identify the causal relationship between national bond interest rates and the green bond market. Using the Toda-Yamamoto approach, the analysis discovered a one-way causal relationship between the interest rate on Germany's 10-year government bonds and the S&P Green Bond Index, but no causal relationship for other national bonds..

Nie et al. (2023) aimed to predict the ChinaBond Green Bond Total Price Index (CGBI). They used an LSTM model with a dataset representing the Chinese green bond market, comprising 1,625 days of data from January 3, 2017, to June 30, 2023. Their analysis found that the returns of other financial assets possess high predictive power for the general and high-frequency components of green bonds.

Zhang and Umair (2023) analyzed the interconnectedness of green finance, including green bonds, renewable energy stocks, and carbon markets using DCC-GARCH VAR. The study found complementary relationships between green bonds and carbon markets and significant dynamic spillover effects between green bonds, renewable energy stocks, and carbon markets.

Kocaarslan and Mushtaq (2024) examined the dynamic connection between the U.S. municipal green bond market and risky assets during COVID-19 using dynamic conditional correlations and machine learning predictions. The study concluded that liquidity risk was a key factor and CatBoost and XGBoost models were more successful.

Liu et al. (2024) examined the interaction between green bond prices and geopolitical risk, concluding that green bond prices were influenced both positively and negatively by geopolitical risk.

Umar et al. (2024) analyzed the return and volatility spillover effects between oil price shocks and green bonds in 12 developed economies using a generalized VAR framework. The study found that price shocks were mostly driven by market network spillovers, with demand-side shocks having more impact on green bonds than supply-side shocks.

Gyamerah and Asare (2024) explored the connection between green bonds and various financial markets and their relationship with global economic uncertainty. The study used PRISMA and found that green bonds interacted with financial markets based on macroeconomic factors and acted as net transmitters of spillovers in the short term and net receivers in the long term during periods of global economic uncertainty.

Zhang and Chen (2024) examined the impact of green bond issuance on stock price crash risk, using various robustness tests, concluding that the impact was heterogeneous.

Liu et al. (2024) examined the impact and heterogeneity of corporate green bond issuance on environmental responsibility, concluding that Chinese enterprises' issuance of green bonds encouraged them to enhance their environmental responsibility.

The literature suggests that markets respond positively to green bonds, improving corporate environmental performance and making green bonds an attractive investment instrument for environmentally conscious investors due to transparency and audit requirements. The scarcity of studies on AI and green bond index prediction is attributed to two factors. Firstly, green bonds are relatively new, leading to an emerging body of literature. Secondly, conservative views on AI usage in the financial sector may prevail in this area.

3. Data and Methodology

The study utilized a total of 693 days of data, spanning from May 6, 2021, to May 2, 2024. The output variable of the study is the "Nikko AM Global Green Bond Fund". Input variables for estimating the output variable were determined as "USD/JPY", "nikkei225", and "west texas spot crude oil price" (wti). In our study, the variables used for green bond index estimation were carefully selected. In the selection of these variables, important economic indicators that are widely used in the literature and can affect green bond prices were taken into account. Exchange rate changes are an important factor affecting the return expectations and investment decisions of international investors. The USD/JPY exchange rate expresses the value of the Japanese yen against the US dollar for investors in Japan, which can indirectly affect the green bond market. Nikkei 225, biggest stock market indices in Japan, reflects the general economic situation and investor confidence. The movements of the index can affect investors' risk appetite and demand for green bonds. Energy prices are another important factor that directly affects the green bond market. Fluctuations in oil prices may affect the financing of energy projects and sustainable energy investments. Nikko AM Global Green Bond Fund is an index that includes green bonds used in the financing of green projects on a global scale. This fund consists of bonds that support sustainability and environmentally friendly projects. The index aims to offer investors attractive returns while fulfilling their environmental responsibilities. The main reason for choosing "Nikko AM Global Green Bond Fund" as the green bond index is that it represents the global green bond market and has the most up-to-date and reliable data in this area. In addition, the performance of the fund reflects the success in financing environmental sustainability projects and therefore constitutes a suitable criterion for our study. These variables and the index are of critical importance for understanding and estimating the dynamics of the green bond market. The reasons for selecting these variables and including the characteristics of the index in the study will increase the integrity of the research and the reliability of the results. The origins of the input and output parameters utilized in the research are displayed in table 3.

Table 3: Sources of the Variables

Variables	Type	Source
JPY/USD	Input	investing.com
WTI	Input	investing.com
Nikkei225	Input	investing.com
Nikko AM Global Green Bond Fund	Output	markets.ft.com

Several deep learning and machine learning models were employed in this research to estimate the green bond index. In the selection of models, methods that have superior performance in analyzing the dynamic, noisy and unstable structure of financial data and have been proven effective in the literature were preferred. Various machine learning models, including Random Forest, MLP, GBR, XGBoost, LSTM, SVR, Catboost, and Linear Regression, were utilized to make predictions based on input variables. The RF is a powerful approach that is a combination of many weak prediction models (decision trees). RF is well recognized for its capacity to capture complex structures and relationships between variables in data sets. The model stands out for its ability to reduce the risk of over-learning and generalize. Therefore, it was chosen to analyze the complexity of financial data and make accurate predictions. MLP is an artificial neural network model widely used in the field of deep learning. Its effectiveness, especially in the prediction of financial time series data, has been frequently emphasized in the literature. The ability of MLP to learn complex relationships between layers is the main reason for using the model in this study. The GBR model produces a robust forecasting model by correcting the errors of successively weaker forecasters. It has been preferred because it successfully captures complex and nonlinear relationships in financial data and generally provides high forecasting reliability. XGBoost is a variant of the Gradient Boosting models, which exhibits superior performance in terms of speed and accuracy. It stands out with its parallel processing capability and over-learning prevention mechanisms. LSTM is a type of RNN that is particularly successful in modeling long-term dependencies. The ability to make future predictions with past information in time series data is the reason for choosing this model. LSTM is frequently used in financial data analysis and is known for its accurate predictions. SVR is based on the principle of linearizing data by moving it to a high-dimensional space. SVR, which has a high generalization ability especially in small data sets, is an effective method for estimating financial time series. CatBoost is a gradient boosting algorithm that stands out with its ability to process categorical data. It was preferred due to its mechanisms to prevent over-learning and its capacity to preserve data diversity. Linear Regression is known for its simplicity and interpretability. The model was included in the study to provide a basic reference point and to compare with other complex methods.

The study's process is depicted in Figure 1 and the parameters utilized in this research are illustrated in Figure 2.

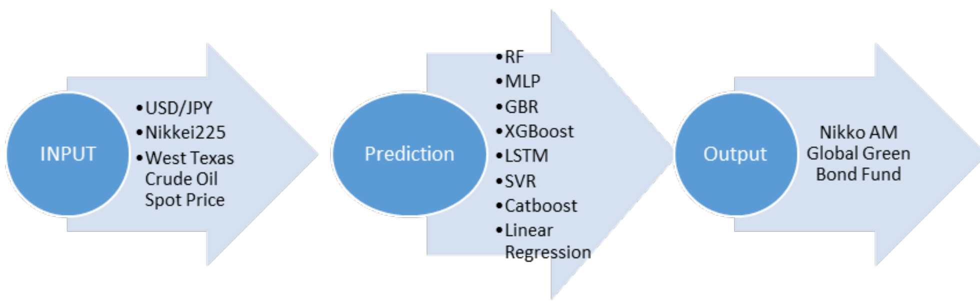


Figure 1: Variables and Approaches Using in This Study

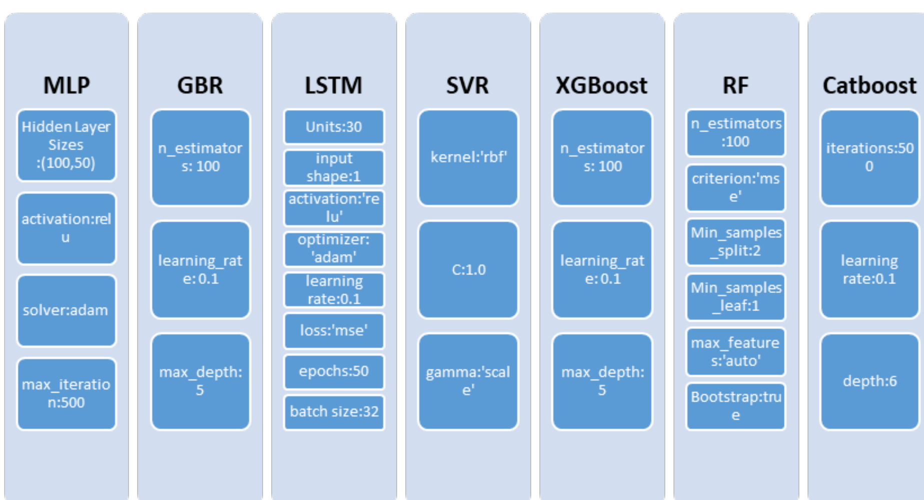


Figure 2: Parameters of The Approaches

3.1. MLP Model

MLP is a type of DFN that is commonly used as a model in the area of deep learning. These models utilize the outputs of the preceding layers as input for the current layer to calculate the output layer from the input layer. This method is widely used for predicting financial time series (Mendoza et al., 2023). MLP is a special sort of ANN that could potentially trained to achieve a certain purpose by adjusting the weights and biases. The input, output, and hidden layers are the three separate layers that comprised the framework. These layers use the supervised backward propagation technique to train their neurons. Multilayer Perceptrons, are specifically engineered to provide an accurate representation of any continuous function and have the capability to tackle issues that cannot be separated by a straight line (Nadirgil, 2023).

The study's parameters revealed that the hidden layer size for the MLP model was determined to be 100.50. This parameter specifies the dimensions of the hidden layers in the MLP model. Each value corresponds to the quantity of neurons present in the hidden layers. Increasing the number of neurons in the model enhances its capacity to comprehend intricate connections, but it also raises the possibility of overfitting. The activation function of choice was "Relu". The "Relu" function is commonly employed in hidden layers. The "ReLU" function maps negative inputs to zero and positive inputs to their original values. By employing this approach, the model's learning process is expedited, and the occurrence of overfitting can be mitigated. The term "Adam" is employed as the solver. The "Adam" solver is a commonly employed optimization algorithm. Adam optimization enhances stochastic gradient descent by incorporating a momentum term and a second moment term. By adopting this approach, the model's training speed is enhanced, leading to improved outcomes. There was a 500-iteration limitation on the maximum number. Each iteration corresponds to a complete run through the training data, and the model is trained using these iterations. The maximum number of iterations determines how long the model training will take. Better model training is possible with more training iterations, but this comes with a price: a longer training period and a higher chance of overfitting.

3.2. GBR Model

An addition to the standard boosting framework, the Gradient Boosting Regression adds a second constraint. The gradient-based residual rate is used to determine which training samples are used in the GBR sequential ensemble procedure. The individual samples are weighted directly based on the magnitude of the error, which ultimately determines the selection fraction throughout the training phase. The choice of base learners typically relies on the underlying problem (Ghosh et al., 2023). In order to create a robust predictive model, the Gradient Boosting Regressor is an ensemble learning technique that combines multiple weak prediction models, usually decision trees. By decreasing the errors of the previous models, iteratively improving the model and producing an incredibly accurate prediction. The technique gradually incorporates decision trees in order to lower a loss function, typically mean squared error. Every tree is constructed to correct the mistakes committed by the ones that came before it. The approach uses gradient descent optimization to determine the most favorable weights for the tree (Chen et al., 2013; Patel et al., 2023). In the GBR model, n estimators are set as 100, learning rate is 0.1 and max_depth is 5. Increased tree density leads to improved generalization and longer training duration. Reducing the learning rate can prolong the training duration but result in a more robust model. Although a higher learning rate can accelerate the model's training, it can also lead to overfitting. The maximum value determines the intricacy and learning potential of each tree. Increasing the max_depth parameter improves the model's ability to understand intricate correlations, but it also increases the likelihood of overfitting.

3.3. LSTM Model

Long Short-Term Memory (LSTM) was created expressly to study and understand information with long temporal links. It is frequently used in the analysis of time series data, including market stock prices. The chronological order of past stock prices and other financial data is referred to as time series data. This data can be analyzed by LSTM, a kind of neural network, to find underlying patterns and trends that can be used to predict future stock values. Because LSTM can process data with many input and output timesteps efficiently, it is a particularly valuable tool for researching stock market data (Gülmez, 2023). LSTM networks possess the capacity to selectively retain patterns across extended sequences. This enables the system to understand the relationship between the data and its previous values, resulting in more precise predictions. LSTM models provide the ability to selectively forget past context in the data and effectively solve the issue of vanishing gradient. The advantages offered by LSTM networks make them a great choice for predicting future stock prices (Md et al., 2023).

The LSTM model employs 30 components. The Units parameter specifies the quantity of neurons employed in the LSTM layer. Greater numbers of neurons enhance the learning capacity of the model but might also lead to overfitting issues. The input shape parameter determines the shape of the data that is sent into the LSTM layer. The activation function is specified as 'relu'. The activation function 'Relu' is commonly employed in deep learning models. This is attributed to its high computing speed and its ability to operate effectively in various scenarios. The 'Relu' function offers superior learning speed in comparison to alternative functions such as 'sigmoid' and 'tanh'. The 'man' optimizer parameter was also utilized in the LSTM model. The individual named 'Adam' demonstrates rapid scalability and possesses the ability to adjust learning rates for various parameters. This facilitates the optimization of various parameters. The epoch is configured to be 50. The epoch is a crucial parameter that defines the duration of the model training process. Increasing the number of training epochs enhances the model's training process, leading to improved prediction outcomes. Nevertheless, very large epoch values can lead to overfitting issues. The batch size refers to the amount of samples that are utilized in each training iteration. Using smaller batch sizes results in reduced memory utilization and faster training when solving the model. This results in the model experiencing increased variation during the training process. Both the training process and the model's performance may be adversely affected by this.

3.4. SVR model

The main idea underlying Support Vector Regression (SVR) is to use a kernel function to convert the difficult nonlinear regression problem in the sample space into a linear regression problem in a high-dimensional space (Zheng et al., 2023). SVM, in contrast to other learning methods, relies on structural risk reduction, which grants it a robust generalization capability. Furthermore, the local optimal point it reaches is also the global optimal solution (Zheng et al., 2021). The performance of the SVR model in practical applications is often strongly influenced by the penalty factor C and the parameter σ of the RBF kernel function. Typically, the parameter C is employed to regulate the complexity of the model. If C is not chosen appropriately, it can lead to a significant increase in model prediction error. Sigma (σ) is a parameter that influences the intricacy of the mapping of the sample feature space and has an impact on the accuracy of the model's predictions. Hence, it is crucial to select appropriate penalty factor and RBF kernel function parameters when constructing the SVR model (Wang et al., 2021).

The SVR model utilizes the radial basis function (RBF) kernel. The kernel function 'rbf' is often utilized. Furthermore, kernels such as 'linear', 'poly', and 'sigmoid' are employed in addition to the 'rbf' kernel. The 'rbf' kernel allows for the transformation of data into a high-dimensional space, enabling the creation of intricate decision boundaries. The C parameter serves as an editing parameter. Increasing the value of C improves the model's ability to accurately represent the training data. Nevertheless, this circumstance poses the danger of overfitting. A lower value of C enhances the model's capacity for generalization. The parameter gamma determines the size of the radial basis function (RBF) kernel. A lower Gamma value enhances the model's ability to generalize, whereas a higher gamma value enables the model to more effectively adjust to the training data.

3.5. XGBoost Model

For stock trend forecasting, Chen and Guestrin's XGBoost model from 2016 was used. This approach is very scalable and is a variation of gradient boosting algorithms. When compared to current tree-based algorithms, our method shows much faster learning speed and improved prediction accuracy because of its parallelization and decentralization characteristics (Han et al., 2023). XGBoost is a type of ensemble model that combines decision trees in an efficient manner to create a more accurate predictive model compared to using individual techniques on an individual basis (Jabeur et al., 2024).

The study utilized the XGBoost model with a value of 100 for the n_estimators parameter. The N estimators parameter determines the quantity of trees utilized in the model. Each tree is generated and incorporated successively throughout the gradient boosting phase. Although this parameter enhances the precision of prediction outcomes, it also elevates the likelihood of overfitting. The learning rate was established as 0.1. This parameter controls the model correction coefficient of each new tree utilized in the model. Increasing the learning rate accelerates the model's learning process, while decreasing the learning rate enhances model stability and improves its ability to generalize. Increasing the learning rate accelerates the prediction process of each new tree in the model and facilitates faster learning. However, it also diminishes the model's ability to generalize. The parameter max_depth is utilized to provide the upper limit for the depth of each individual tree. Increasing the depth of a model allows for more complex feature interactions, but it also raises the danger of overfitting. Furthermore, it also augments the duration of the model's learning process.

3.6. RF Model

The RF model, introduced by Breiman in 2001, is a machine learning model used for classifications and forecast. Unlike a neural network, the RF model is an ensemble learning technique that combines multiple weak decision tree models to create a powerful and accurate prediction model (Xie et al., 2022). The random forest model consists of several decision trees, rendering it well-suited for nonlinear data, and it possesses exceptional anti-overfitting capability (Liu & Ying, 2023). The RF algorithm consists of four training phases. In the first step, k sample sets are extracted from the raw data through k random sampling iterations in order to form decision trees. All of the sample sets are then used as input for each decision tree. Then, each decision tree is given a random feature set and training data set using the bootstrap technique. In phase three, each decision tree is trained. Predictions are produced by the decision tree after training. A test sample makes up the input, while the predicted result is represented in the output. In the end, the Test sets are used as input, and the final output is produced by combining the testing results of each decision tree. For the same test sample, numerous predictions are created in step 3, and the prediction values are pooled in step 4.. During step 3, many predictions are generated for the same test sample, while in step 4, the prediction values are combined by taking their average (Xie et al., 2022).

The value of n_estimators in the random forest model is set to 100. Greater tree density leads to longer training duration. Augmenting the quantity of trees in random forest models does not invariably enhance performance. A quantity of 100 trees is commonly regarded as an equilibrium point. By having a total of 100 trees, we can assure an appropriate amount of variation and prevent overfitting. Additionally, this value serves as a constraint that limits the expansion of the model's solution by incorporating additional trees. The criterion used is mean squared error (MSE). The abbreviation 'mse' is commonly employed to address regression difficulties. The parameter min_samples_split denotes the minimal number of samples required for a node to be eligible for splitting. This enables the model to catch finer details within smaller subgroups, but it also carries the potential danger of overfitting. The value of min_samples_leaf has been set to 1. This approach enables the model to access extremely fine-grained leaf nodes, hence mitigating the problem of overfitting. The max_ feature parameter has been set to "auto". By automatically determining the number of features to be examined in each compartment, the model's variety is increased, and the risk of overfitting is reduced. Bootstrap sampling is used for random sampling, guaranteeing that each decision tree is trained on distinct data subsets. This enhances the model's capacity for generalization.

3.7. Catboost Model

The CatBoost model is an enhanced iteration of the gradient-boosting decision tree technique that effectively handles category features. This algorithm has two primary benefits. Firstly, by handling categorical characteristics during the training phase rather than the preprocessing phase, and secondly, by employing a novel and more efficient schema for computing leaf values during tree structure selection, we can effectively mitigate overfitting (Rastgoo & Khajavi, 2023). The essential characteristic of CatBoost is that the permutations of feature samples preserve the diversity of the linked inputs and mitigate overfitting. The average results are grouped together and transformed into numerical values. This stage deals with categories that have a high level of noise and are characterized by low frequencies. The feature combination undergoes a process of greedy subtree splitting for phrases that are not initially considered by the original trees in the first generation (Massaoui et al., 2020).

The study utilized the Catboost model with 500 iterations. Additional iterations enhance the intricacy and capacity for generalization of the model, although they may also give rise to overfitting issues. The learning rate is a measure of the impact that each individual tree has on the model. The learning rate in the study was set to 0.1. A higher learning rate enhances the learning process but also amplifies the likelihood of overfitting. The value 0.1 is the initial value commonly employed in applications. The depth is measured to be 6. This parameter determines the maximum depth of each individual tree. Although greater depth values have a beneficial impact on understanding intricate connections within the dataset, they also elevate the likelihood of overfitting. A number of 6 in the model typically offers ample flexibility and minimizes the risk of overfitting.

3.8. Performance Evaluation Metrics

The evaluation of the model's performance involved MSE, RMSE; MAE, MAPE and R^2 statistical coefficients. The mathematical formula for calculating the statistical parameters described above are represented by Equations 1, 2, 3, 4, and 5.

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

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

$$MAE = \frac{\sum_{i=1}^{n}|y_i - x_i|}{n} \tag{3}$$

$$MAPE = \frac{\sum_{t=1}^{n}\frac{u_t}{Y_t}}{n} * 100 \tag{4}$$

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \mu)^2} \tag{5}$$

The MSE quantifies the average squared difference between the actual values and the projected values. A smaller MSE represents a higher level of accuracy in the model's predictions, as they are more closely aligned with the actual values. Nevertheless, the MSE amplifies the error values by squaring them, making it challenging to evaluate the actual values based on their scale. RMSE is the square root of MSE. This metric measures the proximity of the error values to the magnitude of the correct values. A smaller RMSE indicates a higher level of accuracy in the model's predictions, as they are more closely aligned with the actual values. MAE calculates the average of the absolute deviations between the actual and anticipated values. MAE provides a more direct representation of the error values' magnitudes and is simpler to interpret compared to MSE. MAPE generates the mean of the absolute percentage deviations among the actual and anticipated values. This measure enables the expression of mistakes as percentages, making it suitable for comparing data across several scales. R2 is the proportion of variation accounted for by the independent variables in the model. Values typically range from 0 to 1. A higher value of 1 indicates a stronger explanation provided by the model for the disparity in the independent variables.

4. Results and Discussion

The purpose of this study was to evaluate how well different deep learning approaches could forecast the Nikko AM Global Green Bond Fund. The assessment of the Nikko AM Global Green Bond Fund utilized the USD/JPY, Nikkei225, and West Texas Crude Oil spot price variables as input. A dataset consisting of the opening prices from 693 days of data. The analysis employing RF, MLP, GBR, XGBoost, LSTM, SVR, Catboost, and LR approaches yielded performance metrics for the training data, which are illustrated in table 4.

Table 4: Statistical Results of Training Data

Train	RF	MLP	GBR	XGBoost	LSTM	SVR	Catboost	LR
MSE	0.00056	0.01169	0.00039	0.00064	0.01038	0.00559	0.00045	0.01511
RMSE	0.02373	0.10811	0.01987	0.02536	0.10190	0.07478	0.02122	0.12291
MAE	0.01570	0.08351	0.01449	0.01799	0.07844	0.05693	0.01650	0.09807
MAPE	0.00235	0.01238	0.00219	0.00271	0.01169	0.00846	0.00247	0.01462
R2	0.99759	0.94997	0.99831	0.99725	0.95555	0.97606	0.99807	0.93533

Table 4 clearly illustrated that the GBR approach produces the smallest values for MSE, RMSE, MAE and MAPE. It also distinguishes itself as a technique with the highest R2 coefficient. These findings show that the GBR model outperforms the other methods when applied to the training dataset. Although the RF model shows similar findings to the GBR model, it produces better MSE, RMSE, MAPE and MAPE values and has a higher R2 value compared to other models. The Catboost model ranks third in terms of prediction accuracy on the training dataset. XGBoost model is observed to produce more successful results compared to the prediction performances of SVR, LSTM, MLP and LR models. Although the prediction results of machine learning techniques such as XGBoost, SVR, LSTM and MLP are satisfactory, they exhibit larger error rates compared to the remaining three models. Finally, the linear Regression model produced the poorest predictions on the training dataset.

The performance metrics for the test data is illustrated in table 5.

Table 5: Statistical Results of Test Data

Test	RF	MLP	GBR	XGBoost	LSTM	SVR	Catboost	LR
MSE	0.00360	0.01031	0.00371	0.00356	0.01030	0.00581	0.00375	0.01421
RMSE	0.06000	0.10153	0.06092	0.05969	0.10148	0.07625	0.06121	0.11922
MAE	0.04276	0.07728	0.04277	0.04336	0.07684	0.05527	0.04493	0.09749
MAPE	0.00634	0.01142	0.00636	0.00644	0.01137	0.00820	0.00664	0.01449
R2	0.98630	0.96078	0.98588	0.98645	0.96082	0.97788	0.98574	0.94592

Upon examination of Table 5, it is evident that the XGBoost model exhibits smaller values for the MSE and RMSE metrics compared to other models, in contrast to the training data set. Simultaneously, it is noted that while it generates higher error coefficients in terms of MAE and MAPE compared to other models, the disparity is minimal. Furthermore, while analyzing the R2 values, it was observed that the XGBoost approach once again yielded the greatest value. The outcome demonstrates that the XGBoost technique outperforms the RF and GBR techniques in elucidating the data. The MLP, LSTM, SVR, Catboost, and LR models exhibited lower predictive performance on the test dataset in comparison to the remaining three models. Upon analyzing the overall table, it is evident that the XGBoost model outperformed other techniques in significant metrics such as MSE, RMSE, and R2. Additionally, it demonstrated comparable outcomes to other methods in terms of MAE and MAPE metrics. Currently, it can be asserted that the XGBoost model exhibits superior adaptability to the test data and yields superior results.

When the metrics of both training and test data are analyzed, it is evident that the error metrics of the GBR model are minimal, but the R2 value is rather high. The results indicate that the GBR model effectively acquires information from the training data. Nevertheless, it was noted that the predictive accuracy declined in the test dataset. It was discovered that the GBR model performed well on the training data but did not perform as well on the test data. These results diminish the model's capacity for generalization. The Random Forest model demonstrated equitable predictive performance on both the training and test datasets. The results demonstrate that the Random Forest model effectively identifies intricate data structures and connections between features. The XGBoost model yielded comparable outcomes to the RF model, although it achieved a superior R2 value in the test data. These results indicate that the XGBoost model exhibits superior generalization capabilities compared to the RF model. The presence of L1 and L2 regularization terms and tree pruning capacity in the XGBoost model may explain these results. Furthermore, the XGBoost model exhibits a slower learning rate compared to the RF model. Despite the longer training period, this characteristic leads to higher precision in the findings. The LSTM, SVR, Catboost, and MLP models exhibited higher levels of prediction inaccuracy compared to tree-based approaches like RF, XGBoost, and GBR. The Linear Regression model yielded the poorest performance for both the training and test data.

Figure 3 shows the training and testing dataset performance of the best performing GBR model.

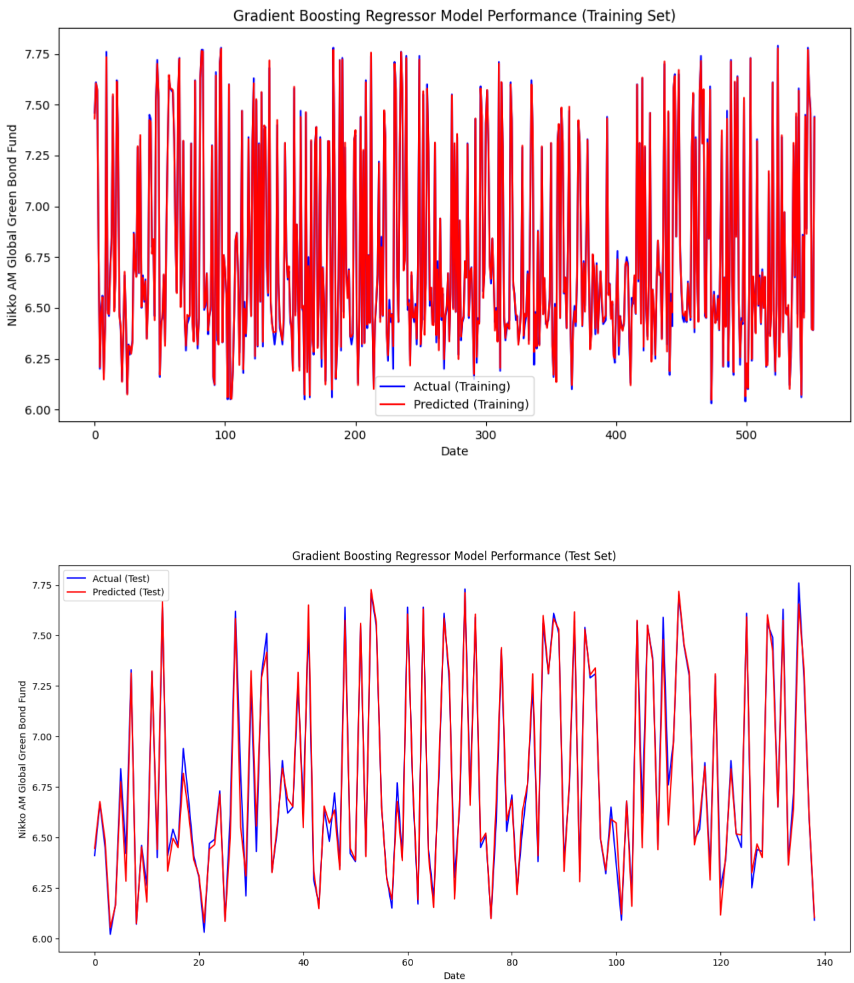


Figure 3: Training and Testing Results of GBR Model

This study can be associated with the study of Çetin (2022), which is one of the artificial intelligence-based studies on green ties in the literatureHowever, Çetin's study solely used artificial neural networks to make predictions; it used the S&P 500 bond index as its sole input. Three distinct inputs were employed in this investigation, and seven distinct machine learning and deep learning algorithms were used to compare the predictions. The research by Kocaarslan and Soytaş (2023) is another study in the literature that looks at how main markets—traditional bonds, equities, and energy commodities markets—affect US municipal green bond performance by taking into account economic risk indicators both before and during COVD19. 4 different machine learning algorithms have been made. The models that produced the best outcomes in this research were the XGBoost and CatBoost techniques, which had the highest R2 value and the lowest MAE, MSE, and RMSE values for the pre – and COVID-19. The successful results of the XGBoost model can be attributed to this study. The analysis by Kocaarslan and Mushtaq (2024) of the dynamic conditional correlations (DCCs) between US municipal green bonds and risky assets (energy commodities and stocks) while taking other macroeconomic risks and uncertainties during the COVID19 crisis period is another study of a similar nature. This study uses three different machine learning methods to look into how the liquidity risk channel affects liquidity risk. With lower MSE and RMSE and higher R2 values, the authors came to the conclusion that CatBoost and XGBoost are more accurate.

5. Conclusions

With the increasing negative effects of climate change on a global scale, environmental protection awareness has increased significantly. Incentives and policies implemented by companies and governments within the framework of social responsibility enable the realization of environmental sustainability projects. Green bonds, which focus on critical issues such as water resource management and climate change, are becoming an important tool for financing environmental projects and promoting sustainability. Green bond issuances increase the likelihood of reducing the carbon footprint and leaving a cleaner and more sustainable living environment for future generations. In this context, green bonds are growing in popularity and importance and contribute to environmental sustainability efforts.

In this study, input variables USD/JPY, Nikkei225 and West Texas Crude Oil spot price variables were used to estimate our output variable, Nikko AM Global Green Bond Fund. The data set was created from the data obtained from the 693-day opening prices of these variables. Then, analysis was made using artificial intelligence-based algorithms RF, MLP, GBR, XGBoost, LSTM, SVR, Catboost and LR approaches. According to the findings obtained from the analysis, it was concluded that the XGBoost model showed superior adaptation to the test data, the GBR model effectively obtained information from the training data, but did not perform well in the test data. In addition, the XGBoost model exhibited superior generalization abilities compared to the RF model, but the XGBoost model exhibited a slower learning rate compared to the RF model. MLP, LSTM, SVR, Catboost and LR models showed lower prediction performance on the test dataset compared to the remaining three models. It was concluded that the Linear Regression model exhibited the lowest performance for both training and test data.

In the literature, the utilization of machine and deep learning methods in green bond market prediction is limited. In this study, green bond index is estimated using various machine learning and deep learning algorithms. This research aims to contribute to the literature by providing a new perspective to green bond forecast. In the study, multiple economic and financial indicators (USD/JPY exchange rate, Nikkei 225 index and WTI crude oil price) were used to estimate the green bond index. Many studies in the literature usually make predictions using a single variable or a limited number of variables. The use of multiple variables in this study contributes to the literature by increasing the accuracy and reliability of the prediction models. In the literature, green bond markets are usually global or limited to certain regions. This study contributes to a better understanding of regional differences and market dynamics by focusing on the green bond market in Japan. The analysis of the green bond market in a large economy like Japan provides important data and findings that will fill the gap in the literature. The study evaluates the performances of various approaches such as RF, MLP, GBR, XGBoost, LSTM, SVR, CatBoost and LR. In the literature, comprehensive comparative analyses on how different models perform in green bond market prediction are limited. This research will contribute to subsequent studies by assessing the efficacy of various models. The objective of this work is to enhance prediction model performance through the application of novel approaches and optimization strategies. Compared to current methods in the literature, this will provide improved accuracy and dependability, which will aid in the development of innovative ways in the forecast of green bonds markets. Consequently, the points where this study is expected to fill the gap in the literature are the use of machine learning, integration of multiple variables, focus on the Japanese market, comparison of model performances and application of innovative methods. With these aspects, the study will fill an important gap in the literature and provide valuable contributions to the research on green bond markets and prediction methods.

As a result, green bonds have been gaining popularity recently. For this reason, investments in this field and the size of green bond indexes are increasing day by day. Thus, accurate predictions of green bonds are very important for both individual and institutional investors. As mentioned above, the number of studies in the literature on green bond estimation is quite limited. This study attempted to fill this gap in the literature. In the study, USD/JPY, West Texas Crude Oil Price and Nikkei225 variables were selected as input variables. However, the study can be enriched by using different variables affecting Green Bond prices. In particular, macro variables such as inflation, interest rates and GDP can be used to better predict green bond prices. The main problem here is that Green bond indexes emerged in the late 2000s and the accessible data set is limited. Data on variables such as inflation, interest rates and GDP are generally published monthly. If older data on Green Bond Indexes are found in future studies, the data set can be expanded to include macro variables in the study and more accurate results can be obtained. In addition, the use of hybrid methods in index prediction in the literature can increase the prediction abilities of the models. In future studies, prediction performance can be increased by recommending hybrid methodologies in addition to the methods used in this study.

Green bonds, which have sustainable investment features, are preferred by investors. For this reason, green bonds are an important component for large asset allocation. The Ministry of Treasury and Finance announced that Turkey's first green bond issuance was carried out in 2023. According to the statement of the Ministry, they announced that the July 13, 2030, maturity transaction, which was realized for a consistency of 2.5 billion USD, resulted in a return rate of 9.30%. It is of great importance to estimate green bond issuances in order to determine the most cost-effective conditions for issuing these bonds among various risk factors.

Green transformation will ensure energy sovereignty, employment creation and economic development. Since 2007, the green bond market has been expanding with investor support. Policy makers can benefit from private capital flows to finance development and infrastructure by greening investments and development plans. Market integrity, strategic issuance (green city bonds, green bonds from green and development banks, green government bonds), market development (green storage, green covered bonds), improvement of the risk-return profile, tax incentives for emitters and investors and increasing demand for green bonds can also be foreseen as policy areas assisting in the market expansion for green bonds.

References

Adekoya, O. B., Abakah, E. J., & Oliyide, J. A. (2023). Factors behind the performance of green bond markets. *International Review of Economics & Finance*, *88*, 92-106.

Bachelet, M. J., Becchetti, L., & Manfredonia, S. (2019). The green bonds premium puzzle: The role of issuer characteristics and third-party verification. *Sustainability,* 11(4), 1098.

Chatziantoniou, I., Abakah, E. J. A., Gabauer, D., & Tiwari, A. K. (2022). Quantile time–frequency price connectedness between green bond, green equity, sustainable investments and clean energy markets. *Journal of Cleaner Production*, 361, 132088.

Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. *In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). New York, NY, USA: Association for Computing Machinery. https://doi.org/10.1145/2939.672.2939785

Climate Bonds Initiative Report, (2024a). https://www.climatebonds.net/resources/reports/quarterly-market-update-q1-2024, Access Date:03.08.2024

Çetin, D. T. (2022). Green bonds in climate finance and forecasting of corporate green bond index value with artificial intelligence. *Journal of Research in Business,* 7(1), 138-157.

Dumlu, T., & Keleş, E. (2023). Kurumsal Yeşil Tahviller ve Firma Değeri: Türkiye Uygulamaları. *Finans Ekonomi ve Sosyal Araştırmalar Dergisi*, 8(1), 261-269.

Flammer, C. (2021). Corporate green bonds. *Journal of Financial Economics,* 142(2), 499-516.

Ghosh, I., Alfaro-Cortés, E., Gámez, M., & García-Rubio, N. (2023). Prediction and interpretation of daily NFT and DeFi prices dynamics: Inspection through ensemble machine learning & XAI. *International Review of Financial Analysis*, 87, 102558.

Gülmez, B. (2023). Stock price prediction with optimized deep LSTM network with artificial rabbits optimization algorithm. *Expert Systems with Applications*, 227, 120346.

Güneş, H. (2023). Yeşil tahvil ve ülke tahvilleri arasındaki nedensellik. *Karamanoğlu Mehmetbey Üniversitesi Sosyal Ve Ekonomik Araştırmalar Dergisi*, 25(45), 1244-1263.

Gyamerah, S. A., & Asare, C. (2024). The impacts of global economic policy uncertainty on green bond returns: A systematic literature review. *Heliyon*, *10*(3), e25076. https://doi.org/10.1016/j.heliyon.2024.e25076

Hachenberg, B., & Schiereck, D. (2018). Are green bonds priced differently from conventional bonds?. *Journal of Asset Management*, 19(6), 371-383.

Han, Y., Kim, J., & Enke, D. (2023). A machine learning trading system for the stock market based on N-period Min-Max labeling using XGBoost. E*xpert Systems with Applications,* 211, 118581.

ICMA (International Capital Market Association) (2021). Sürdürülebilirlik Tahvili Rehberleri https://www.icmagroup.org/assets/documents/Regulatory/Green-Bonds/Translations/2021/Turkish-SBG-2021.pdf?vid=2. . Access.Date:07.05.2024

Jabeur, S. B., Mefteh-Wali, S., & Viviani, J. L. (2024). Forecasting gold price with the XGBoost algorithm and SHAP interaction values. *Annals of Operations Research*, 334(1), 679-699.

Kocaarslan, B., & Soytas, U. (2023). The role of major markets in predicting the US municipal green bond market performance: New evidence from machine learning models. *Technological Forecasting and Social Change,* 196, 122820.

Kocaarslan, B., & Mushtaq, R. (2024). The impact of liquidity conditions on the time-varying link between US municipal green bonds and major risky markets during the COVID-19 crisis: A machine learning approach. *Energy Policy*, 184, 113911.

Kurtoğlu, S., & Çakan, C. D. (2022). Sürdürülebilir Ekonomide Yeşil Tahvil ve Bir Türkiye Örneği. International Journal of Disciplines in Economics & Administrative Sciences Studies, 8(44), 523-534.

Liu, F., Qin, C., Qin, M., Stefea, P., & Norena-Chavez, D. (2024). Geopolitical risk: An opportunity or a threat to the green bond market?. *Energy Economics,* 107391.

Liu, M., & Ying, Q. (2023). The role of online news sentiment in carbon price prediction of China's carbon markets. *Environmental Science and Pollution Research*, 30(14), 41379-41387.

Liu, Y., Huang, H., Mbanyele, W., Wang, F., & Liu, H. (2024). Does the issuance of green bonds nudge environmental responsibility engagements? Evidence from the Chinese green bond market. *Financial Innovation*, 10(1), 92.

Lukšić, I., Bošković, B., Novikova, A., & diğerleri. (2022). Innovative financing of the sustainable development goals in the countries of the Western Balkans. *Energy, Sustainability and Society, 12*(15). https://doi.org/10.1186/s13705.022.00340-w

Md, A. Q., Kapoor, S., AV, C. J., Sivaraman, A. K., Tee, K. F., Sabireen, H., & Janakiraman, N. (2023). Novel optimization approach for stock price forecasting using multi-layered sequential LSTM. *Applied Soft Computing*, 134, 109830.

Mendoza, C., Kristjanpoller, W., & Minutolo, M. C. (2023). Market index price prediction using Deep Neural Networks with a Self-Similarity approach. *Applied Soft Computing*, 146, 110700.

Nadirgil, O. (2023). Carbon price prediction using multiple hybrid machine learning models optimized by genetic algorithm. Journal of Environmental Management, 342, 118061.

Nie, Q., Chen, S., Chen, Y., & Hu, Y. (2023). Integrated prediction of green bond return under the dual risks of climate change and energy crisis. *Frontiers in Environmental Science*, *11*, 1336867.

Nikko Asset Management (nikko am), (2024). https://en.nikkoam.com/ . Access.Date:08.05.2024

Patel, T., & Sahu, J. (2023, October). Comparative analysis of regression techniques for accurate house price prediction using machine learning: a statistical analysis method. *In 2023 IEEE International Conference on Blockchain and Distributed Systems Security (ICBDS)* (pp. 1-6). IEEE.

Piñeiro-Chousa, J., López-Cabarcos, M. Á., Caby, J., & Šević, A. (2021). The influence of investor sentiment on the green bond market. *Technological Forecasting and Social Change*, 162, 120351.

Rastgoo, A., & Khajavi, H. (2023). A novel study on forecasting the airfoil self-noise, using a hybrid model based on the combination of catboost and arithmetic optimization algorithm. *Expert Systems with Applications*, 229, 120576.

T.C. Enerji ve Tabii Kaynaklar Bakanlığı. (2024). Elektrik üretiminde yenilenebilir enerji kaynaklarının payı arttı. April 1, 2024, Retrivied from https://enerji.gov.tr/haber-detay?id=21270 adresinden erişildi.

Turan, N. (2022). Yeni bir borç enstrumani olarak yeşil tahviller: global piyasalar ve türkiye'deki mevcut durum üzerine tespitler. *Sayıştay Dergisi*, 33(125), 311-341.

Turguttopbaş, N. (2020). Sürdürülebilirlik, yeşil finans ve ilk türk yeşil tahvil ihraci. *Finansal Araştırmalar ve Çalışmalar Dergisi,* 12(22), 267-283.

Umar, Z., Hadhri, S., Abakah, E. J. A., Usman, M., & Umar, M. (2024). Return and volatility spillovers among oil price shocks and international green bond markets. *Research in International Business and Finance,* 69, 102254.

Wang, X., Gao, S., Zhou, S., Guo, Y., Duan, Y., & Wu, D. (2021). Prediction of house price index based on bagging integrated WOA-SVR model. *Mathematical Problems in Engineering,* 2021, 1-15.

Wang J., Tang J. & Guo K. (2022). Green bond index prediction based on CEEMDAN-LSTM. *Front. Energy Res.* 9:793413. doi: 10.3389/fenrg.2021.793413

Wasserbacher, H., & Spindler, M. (2022). Machine learning for financial forecasting, planning and analysis: Recent advances and pitfalls. *Digital Finance,* 4, 63–88. https://doi.org/10.1007/s42521.021.00046-2

Xie, Q., Hao, J., Li, J., & Zheng, X. (2022). Carbon price prediction considering climate change: A text-based framework. *Economic Analysis and Policy*, 74, 382-401.

Yağcılar, G. G., & Yilmaz, F. (2022). Yeşil tahvil ihraci duyurularina pay senedi yatirimcilarinin tepkisi: türkiye'deki bankalarin yeşil tahvil ihraçlarina ilişkin olay çalişmasi. Journal of *Business Innovation and Governance*, 5(2), 147-162.

Zerbib, O. D. (2019). The effect of pro-environmental preferences on bond prices: Evidence from green bonds. *Journal of banking & finance*, 98, 39-60.

Zhang, Y., & Umair, M. (2023). Examining the interconnectedness of green finance: an analysis of dynamic spillover effects among green bonds, renewable energy, and carbon markets. *Environmental Science and Pollution Research,* 30(31), 77605-77621.

Zhang, Y., Li, Y., & Chen, X. (2024). Does green bond issuance affect stock price crash risk? Evidence from China. *Finance Research Letters,* 60, 104908.

Zheng, J., Wang, Y., Li, S., & Chen, H. (2021). The stock index prediction based on SVR model with bat optimization algorithm. *Algorithms*, 14(10), 299.

Zheng, Y., Luo, J., Chen, J., Chen, Z., & Shang, P. (2023). Natural gas spot price prediction research under the background of Russia-Ukraine conflict-based on FS-GA-SVR hybrid model. *Journal of Environmental Management*, 344, 118446.

Zhou, X., & Cui, Y. (2019). Green bonds, corporate performance, and corporate social responsibility. *Sustainability*, 11(23), 6881.