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Research Article

Forecasting of the Biofuel Consumption Trend on a European Scale with the Random Forest Algorithm

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Abstract
Globally, energy demand is continuously increasing due to population growth, economic development, and industrialization. Alongside this rising demand, concerns regarding the environmental impacts of fossil fuels have increased the demand for renewable and clean energy. In the global transition to renewable energy, biofuels play a crucial role. Therefore, accurate biofuel forecasting is critical for shaping regional policies. This enables policymakers to allocate countries' resources according to strategic goals, plan the necessary infrastructure and support economic growth. In this study, a forecasting model was developed using the Random Forest Algorithm (RFA) to predict the consumption trends of biofuels. Therefore, statistical data for the European region (including Total Europe and Other Europe) from 1992 to 2022 were first collected. Then, these values were forecasted for the years 2025, 2030, and 2050. The values obtained from the forecasting model created with RFA showed the highest successful results when the number of decision trees was 50, with R^2 value of 0.9975. The results of the analysis demonstrated that the models created for Europe could be used in renewable energy projections for future planning. All results were thoroughly analyzed, and measures/requirements that could be taken in line with the European Union Green Deal were discussed.

Keywords
Energy, biofuel, prediction, random forest algorithm

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1. Introduction

With population growth and technological innovations, the diversification of production and consumption has steadily increased energy demand from the past to the present. In the face of this rising demand, the rapid depletion of fossil fuels and the challenges of accessing new sources have further emphasized the importance of renewable alternative energy sources to ensure sustainability in energy supply. The fluctuating prices of current fossil fuels, the production of greenhouse gases and other harmful emissions that contribute to global warming and environmental pollution, have accelerated the development of sustainable, clean, and renewable energy technologies. Especially after the global energy crisis that has persisted since the 1970s, many developed and developing countries have turned to renewable energy sources and prioritized increasing the share of renewable energy in the energy supply-demand balance (Reid et al., 2020; Verma et al., 2022).

Renewable energy sources are those that are constantly replenished in nature and do not carry the risk of depletion. Unlike fossil fuels, these energy sources cause less harm to the environment and provide sustainable energy production. Renewable energy sources can be exemplified by solar energy, wind energy, hydroelectric energy, geothermal energy, biomass energy, and wave-tidal energy. Because these sources are sustainable, they reduce environmental impacts and decrease dependence on fossil fuels (International Renewable Energy Agency, 2023).

In the transition process to renewable energy, biofuels play a significant role worldwide. The concepts of biomass, biofuels, and bioenergy are broad and interact with each other. Biofuels are a type of energy obtained by converting biomass into fuel form through various biochemical or thermochemical processes. Biomass consists of organic materials from plant or animal sources and is used as raw material in bioenergy production. Organic components such as vegetable oils, starch, sugar, and cellulose are processed to produce bioethanol, biodiesel, and biogas. In summary, biomass forms the source for the bioenergy production process, while biofuels are the final products obtained from this process and used in energy production (Sözen et al., 2017).

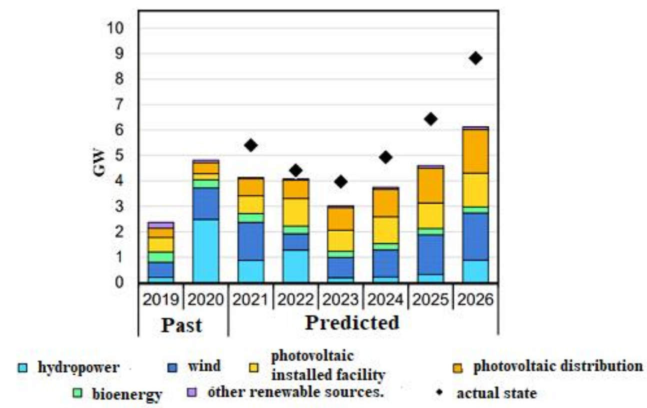
Today, for countries like Turkey that are dependent on external energy sources, there is an increasing shift towards bioenergy sources that can be obtained from biomass due to disadvantages such as the rising production costs of fossil energy sources and issues with the continuity of energy supply (Aydın-Kandemir & Sarptaş, 2022). Specifically in Turkey, increasing the amount and diversity of energy that can be obtained from biomass resources has been set as a strategic goal for the country’s sustainable economic development (Topal & Arslan, 2008). By 2030, Turkey aims to significantly increase the share of renewable energy in the global energy mix and ensure access to locally available, reliable, sustainable, and modern energy in the region. To achieve this goal, national policy needs to focus on the widespread use of renewable energy sources for electricity generation, ensuring that these sources are integrated into the economy in a reliable, economical, and high-quality manner, increasing resource diversity, reducing greenhouse gas emissions, utilizing waste, protecting the environment, and developing the manufacturing sector necessary to realize these objectives (T.C. Strategy Department, Sustainable Development Goals Evaluation Report, 2019). In parallel with the globalized world, making realistic forecasts regarding regional energy supply and demand will not only guide decision-making institutions in the energy sector but also provide crucial information to regional entrepreneurs considering investments in this field, thereby contributing to energy security. Determining biofuel consumption trends at the European scale is critical for Turkey's renewable energy transition process due to its geographical location. Considering the European Green Deal, which aims to make Europe the first climate-neutral continent by 2050 and reduce carbon emissions by 55% by 2030, biofuels emerge as a significant potential that should be thoroughly examined for regional sustainability goals. Since biofuels are generally produced from agricultural products, regional biofuel demand data can assist governments and policymakers in shaping agricultural policies; in this context, it will also guide the positioning of infrastructure such as management of agricultural lands, sustainable farming practices, biofuel refineries, storage facilities, and distribution networks.

This study uses biofuel consumption data from Turkey between 1992 and 2022 to make a projection of the potential biofuel consumption in the near future, based on the European scale. For this purpose, the Random Forest algorithm was used to predict future biofuel consumption data. The Random Forest algorithm, a community learning method consisting of decision trees, is widely used in both classification and regression tasks, and was preferred in this study to provide realistic data for future projections due to its high prediction accuracy, versatility, good generalization capability, and resistance to overfitting (Fawagreh et al., 2014; Probst et al., 2019; Fan et al., 2022). Therefore, the algorithm created using past and current biofuel consumption data was validated with the current data (for the year 2022), and projections for the years 2025, 2030, and 2050 were made.

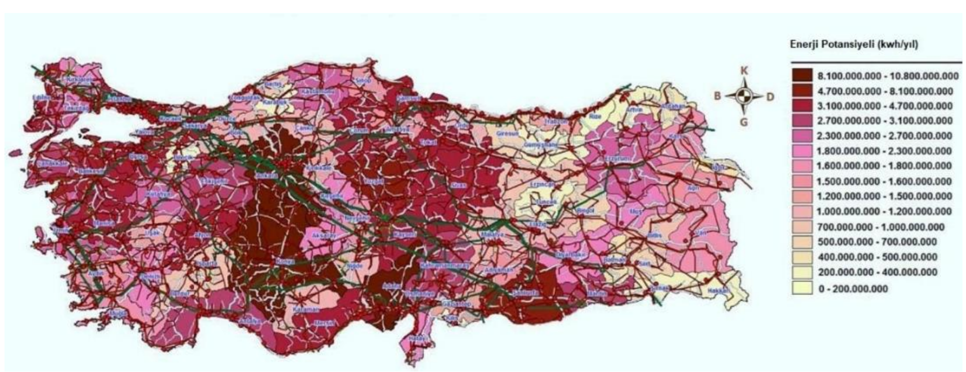
2. Renewable Energy, Global Analysis of Bioenergy Usage, and Turkey's Current Position

A renewable energy source is an energy source that is "renewed as much as it is consumed." These sources can be considered alternative energy sources only when they are transformed into forms that can replace the demand met by fossil fuels, and this transformation is achieved sustainably (Seydioğulları, 2013). Bioenergy is defined as a versatile resource among renewable energy sources because it can be used in all consumption sectors such as heating, electricity, and transportation. Additionally, the storage and processability of biomass and biofuels make them usable regardless of weather conditions or seasons, unlike wind and solar energy. Therefore, bioenergy can provide continuity in energy supply compared to intermittent renewable sources. Biomass is considered one of the most promising energy sources to replace the fossil fuels used today, as synthetic fuels can be produced from biomass in solid, liquid, and gas phases. Furthermore, the use of agricultural residues and organic waste as substrates in biofuel production contributes to waste management and reduces greenhouse gas emissions from landfills (Sarker et al., 2023; Özsin et al., 2019; Özsin & Pütün, 2017).

When the current status and future position of Turkey's renewable electricity capacity are examined by the International Energy Agency, as seen in Figures 1 (a) and (b), it is expected that the share of renewable energy will increase by 26 GW or more than 53% during the 2021-2026 period, and it is known that the biomass potential varies geographically among provinces. (International Energy Agency (IEA), 2021; Renewables 2021: Analysis and Forecasts to 2026. Paris: IEA). However, compared to other renewable energy sources, bioenergy's role in Turkey in terms of installed capacity remains behind hydroelectric, geothermal, and wind energy. Table 1 summarizes the data from the Turkey Biomass Energy Potential Atlas (BEPA) prepared by the General Directorate of Renewable Energy of the Ministry of Energy and Natural Resources. The results show that more than 34x10^6 TEP of energy could be obtained annually from waste biomass sources in Turkey. Furthermore, Turkey's climate and land conditions are highly suitable for energy crop cultivation, and due to widespread agricultural production and livestock farming, the country contains significant amounts of agricultural and animal waste (Senocak & Goren, 2022). Therefore, determining the quantity and distribution of the country's biomass resources, positioning biorefineries in provinces according to regional biomass potential, and contributing to future energy policies through this process are of great importance. On a global scale, it is known that the current annual production capacity of advanced biofuels is less than 1 billion gallons worldwide. As a result, it is essential to design and develop many sustainable and biomass-bioenergy supply chains that link sustainable biomass feedstock and final fuel/energy products in a way that provides lower costs, less environmental impact, and greater social benefits. In this context, to accelerate the transition to large-scale and sustainable production and use of biofuels and bioenergy products, bioenergy systems must be systematically designed and optimized (Yue et al., 2014).



(a)



(b)

Figure 1. (a) Forecast of Turkey's Renewable Energy Sources by the International Energy Agency (IEA) (Interatomic Energy Agency (IEA), 2021. Renewables 2021: Analysis and Forecasts to 2026) and **(b)** Biomass Potential by Province (İlleez, 2020).

Table 1. Current Energy Equivalents of Biomass Resources in Turkey (TOE/year)
(Source: https://bepa.enerji.gov.tr/)

Biomass Source	Theoretical Energy Equivalent	Economic Energy Equivalent
Animal Waste	4,385,371	1,084,506
Plant-Based Waste	25,384,268	1,462,159
Municipal Waste	3,373,011	485,858
Forest Residuals	859,899	-
Total Energy Equivalent of Wastes	**34,002,549**	-

3. Data Set and Method Used in the Study

3.1. Data set

In this study, the data set used comprises "Biofuel consumption" data (in petajoules, PJ) from the "Energy Institute Statistical Review of World Energy" reported in 2023 (The report can be accessed at https://www.energyinst.org/statistical-review). In the report, OECD member countries located in the European continent are defined as "European Countries," while other countries in the continent are referred to as "Other European Countries". The report includes complete data for the following European countries: Austria, Belgium, Finland, France, Germany, Italy, the Netherlands, Poland, Portugal, Spain, Sweden, and the United Kingdom. The "Other European Countries" category comprises Albania, Bosnia and Herzegovina, Bulgaria, Croatia, Cyprus, North Macedonia, Georgia, Gibraltar, Latvia, Lithuania, Malta, Montenegro, North Macedonia, Romania, and Serbia.

Data related to European and Other European Countries, as classified in the report, were analyzed and processed in this paper. Analyses were conducted using the Random Forest Algorithm (RFA) by using the Orange software. Initially, predictions were made using the RFA based on historical data from 1992 to 2022, and the algorithm's performance was tested against actual data. Subsequently, hyperparameter optimization was performed on the predictive model to determine the impact of the number of trees, and statistical metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE) were utilized to evaluate model performance. This comprehensive evaluation allowed for a more detailed assessment of the model's performance, and biofuel consumption trends for the near future (2025, 2030, and 2050) were estimated.

3.2. Random Forest Algorithm

The Random Forest Algorithm (RFA) (Breiman, 2001) is a widely used machine learning technique in the literature for classification and regression problems. This algorithm operates using decision trees as its fundamental units. Decision trees create a model that classifies or predicts a dataset based on input features. However, since a single decision tree can often have high variance and low predictive power, RFA is preferred to mitigate these weaknesses. RFA works by generating multiple decision trees from a dataset; each tree is trained on a randomly sampled subset of the dataset. Additionally, during the growth of these trees, a randomly selected subset of features is used. This approach ensures that each decision tree observes different subsets of features and data points. Once each tree is independently trained, the predictions of all trees are aggregated, typically by averaging for regression tasks or taking the mode for classification tasks. This ensemble approach helps to offset the errors of individual trees, resulting in a more robust and balanced model. Random forests generally perform well on high-dimensional and complex datasets. They are also resistant to overfitting and offer advantages such as the ability to assess variable importance and handle missing data (Rodriguez-Galiano et al., 2015).

Compared to global machine learning models like Artificial Neural Networks (ANNs) or Support Vector Machines (SVMs), which attempt to create a single global model from the data, ensemble learning models such as RFA, which construct and aggregate multiple models, often perform better when dealing with complex systems. RFA employs two main strategies: Bagging (Breiman, 1996) and the Random Subspace Method (Ho, 1998). All base learners in RFA are classification and regression trees (CART). The general flow of the RFA algorithm is illustrated in Figure 2.

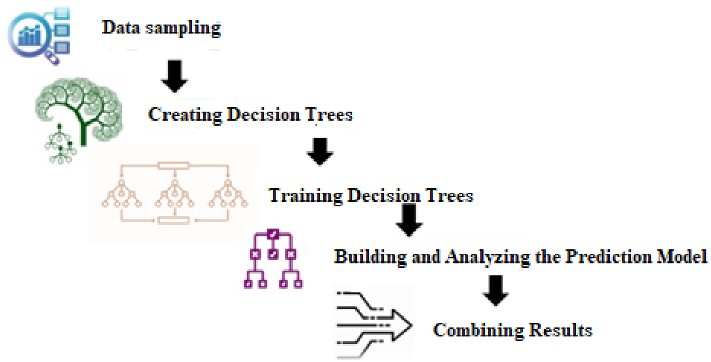


Figure 2. General Flow of the Random Forest Algorithm (RFA)

Random Forest Algorithm (RFA) demonstrates several advantages over other prediction tools and algorithms in many cases. Since RFA operates by combining multiple decision trees, it generally provides higher accuracy compared to a single decision tree. Each decision tree is trained on different subsets of data, enhancing the overall predictive performance of the model. Additionally, the ability of random forests to work with both numerical and categorical data makes it applicable to problems with diverse data types. Furthermore, RFA handles non-linear and non-Gaussian data effectively, is suitable for model interpretation, and avoids overfitting as the number of trees increases. The algorithm is also known to provide a measure of the relative importance of predictors, which can be useful for variable selection (Islam et al., 2023; Li et al., 2020; Wang et al., 2018). Therefore, RFA can be effectively used in prediction models for both classification and regression problems when paired with appropriately chosen parameters (hyperparameter optimization).

At its core, RFA involves three steps. The first step utilizes the stochastic nature of the algorithm to create n different training sample sets for n CARTs (Classification and Regression Trees) using the bootstrap sampling technique, also known as sampling with replacement. In the second step, the random subspace technique is applied. Finally, in the third step, for each node in each CART, partial features are randomly selected from all input features. This process builds a predictive model using RFA.

Studies in which RFA has been used for forecasting in the energy field, leveraging the algorithm's superior predictive performance and high adaptability, are well-documented in the literature. Specifically, RFA has been successfully applied in areas such as energy consumption forecasting, energy efficiency analysis, renewable energy production prediction, and energy market analysis. For example, Meng and Song (2020) used RFA to forecast daily photovoltaic power generation during winter in northern China. Lin et al. (2015) applied RFA to predict wind speed and direction, which are critical for grid management. Reported results emphasized improved prediction accuracy. Torres-Barrán et al. (2019) examined the application of RFA, gradient-boosted regression, and extreme gradient boosting methods to global and local wind energy forecasting, as well as to a solar radiation problem. Tharani et al. (2020) investigated the prediction of energy generation from non-conventional sources such as wind and solar to transition to renewable energy efficiently without disrupting grid balance. They compared the efficiency of linear regression, neural network regression, random forest regression, and extra tree regression models in estimating global solar radiation. Assouline et al. (2018) presented a novel hybrid methodology combining geographical information systems, solar models, and random forests to estimate rooftop photovoltaic solar energy potential on a national scale. They employed a hierarchical approach that divides the final potential estimation into several steps. Fan et al. (2022) proposed a model that hybridizes the random forest model and mean-producing function model for short-term accurate load forecasting, which is essential for the planning and operation of transportation systems. Their modeling process used input variables such as a time variable, a random forest prediction value, and an average prediction value. Meenal et al. (2022) provided a comprehensive overview of existing and emerging developments in solar and wind prediction techniques for renewable energy systems in smart grids. They discussed the performance of various forecasting models, including physical models, statistical models, artificial intelligence-based models, machine learning, and deep learning models.

As seen in mentioned papers above, RFA is a widely preferred method in various forecasting and analysis applications in the energy sector. By using this algorithm, the energy industry can make data-driven decisions and achieve more efficient and sustainable energy management.

4. Computational Results of The Random Forest Algorithm

The prediction models developed using the Random Forest Algorithm (RFA) achieved an R^2 value of approximately 0.998. This value measures the proportion of variation in the dependent variable that can be explained by the independent variables in the model, essentially representing the square of the correlation coefficient.

Additionally, the model's error metrics were calculated as follows:

- Mean Squared Error (MSE): 129.529
- Root Mean Squared Error (RMSE): 11.381
- Mean Absolute Error (MAE): 6.288

In Table 2, the analysis of European countries for the years 1992–2022 is presented, while Table 3 provides the same analysis for other European countries during the same time period. As observed from the tables, the predicted values closely matched the actual values in most years. However, in some years (e.g., 2003, 2004, and 2005 in Table 3), the differences between predicted and actual values were more significant. Nevertheless, considering the overall performance of the model, the results and the high R^2 value demonstrate the predictive success of the algorithm.

Table 2. Analysis of European Countries Using RFA Between 1992–2022

European Countries - Biofuel Consumption (PJ)		
Years	**Biofuel Actual Data**	**Prediction Result with RFA**
1992	0.843816	2.83964
1993	2.01661	3.26967
1994	5.52989	5.91252
1995	8.6861	8.58013
1996	12.7927	12.492
1997	17.4868	16.4658
1998	16.2537	16.6035
1999	18.2985	18.0688
2000	28.5781	26.9966
2001	33.1586	31.3846
2002	43.7677	39.2654
2003	55.4494	55.4786
2004	73.7325	74.6473
2005	128.404	110.462
2006	200.302	179.881
2007	278.685	261.245
2008	382.561	350.012
2009	452.9	437.714
2010	537.37	504.995
2011	568.344	540.321
2012	617.28	583.128
2013	563.745	574.462
2014	601.259	587.26
2015	602.855	604.492
2016	609.363	611.482
2017	658.222	640.482
2018	718.854	703.843
2019	744.963	741.982
2020	762.268	758.389
2021	786.326	783.465
2022	855.9	819.141

Table 3. Analysis of RFA of Other European Countries Between 1992-2022

Other European Countries - Biofuel Consumption (PJ)		
Years	**Biofuel Actual Data**	**Prediction Result with RFA**
1992	0.0715783	0.169959
1993	0.153511	0.210925
1994	0.293022	0.329921
1995	0.662993	0.595998
1996	0.918302	0.896542
1997	1.34858	1.29272
1998	1.46745	1.44419
1999	1.83932	1.77074
2000	2.50382	2.41112
2001	3.11151	3.97286
2002	2.74657	4.16091
2003	2.60803	7.50738
2004	1.36867	9.9654
2005	0.912458	13.8248
2006	7.05159	10.7792
2007	17.2968	19.2683
2008	34.8453	31.4862
2009	43.123	43.3696
2010	49.6262	49.7965
2011	59.4157	58.6375
2012	69.1899	68.7598
2013	85.2727	79.8927
2014	81.505	82.6926
2015	83.6893	86.781
2016	94.3355	93.1717
2017	109.166	104.938
2018	114.933	111.749
2019	134.01	127.053
2020	137.664	136.119
2021	139.597	138.739
2022	143.676	141.515

The predicted values for 2025, 2030, and 2050 are provided in Table 4 for "European countries" and in Table 5 for "Other European countries". The trend of actual data and forecasted data obtained with RFA is shown in Figure 3. As seen in Table 4, the biomass consumption amount for European countries is calculated as 821,598 PJ for 2025, while these values are 1,090,569 PJ and 1,895.46 PJ for 2030 and 2050, respectively. For other European countries, these values are calculated as 155.722 PJ, 74.954 PJ, and 288.96 PJ, respectively. The number of trees used in these forecasting models was determined to be 50, based on hyperparameter optimization.

Table 4. Prediction Results for 2025, 2030, and 2050 Found By RFA for European Countries

European Countries - Biofuel Consumption (PJ)	
Year 2025	821.598
Year 2030	1090.569
Year 2050	1895.46

Table 5. Forecast Results for 2025, 2030, and 2050 Found By RFA for Other European Countries

Other European Countries - Biofuel Consumption (PJ)	
Year 2025	155.722
Year 2030	174.954
Year 2050	288.96

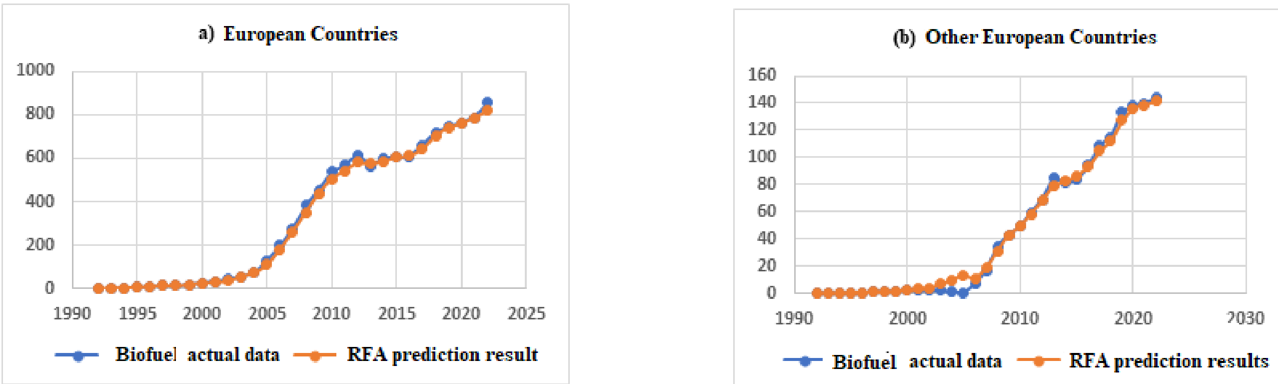


Figure 3. (a) Actual and Forecast Data Curve for European Countries (1992–2022); (b) Actual and Forecast Data Curve for Other European Countries (1992–2022)

The optimization of the parameters used in the algorithm is crucial. In the Random Forest algorithm, the parameter "number of trees used" significantly affects the results. The R^2 values obtained for different numbers of trees are shown for both datasets in Table 6. In Figure 4, the variation in R^2 values for different numbers of trees, as presented in Table 6, is depicted. While R^2 measures how well the model fits the data, MAE, MSE, and RMSE measure the magnitude of prediction errors. Therefore, it is important to use these metrics together to comprehensively evaluate the performance of the model. MAE calculates the average of the absolute values of prediction errors, whereas MSE and RMSE calculate the mean of the squares of these errors. For this reason, MAE provides a more balanced error measure, while MSE and RMSE place greater emphasis on larger errors.

Table 6. Comparison of RFA General Forecast Model Performance in Terms of R^2 for Different Hyperparameter Values

	MSE	RMSE	MAE	R^2
# of trees =10	253.37	15.9	7.77	0.9766
# of trees =15	162.55	12.73	6.31	0.9899
# of trees =20	175.45	13.22	7.08	0.9917
# of trees =25	236.6	15.3	8.01	0.9930
# of trees =30	240.93	15.52	7.11	0.9945
# of trees =50	180.262	13.45	6.83	0.9975
# of trees =100	199.7	14.13	7.1	0.9971

In Figure 4 below, a visualization of the comparison of the MSE, RMSE, MAE, and R^2 values obtained from the analysis is presented.

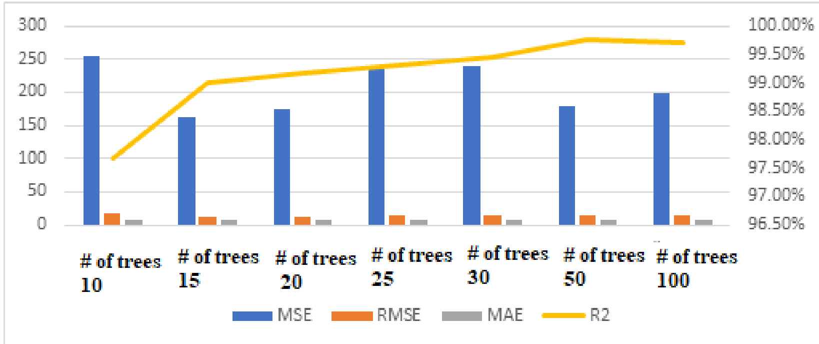


Figure 4. Comparison of MSE, RMSE, MAE, and R^2 Values for Different Numbers of Trees

In Figure 5, the variation of the multiple explanatory coefficient based on the number of decision trees is presented. This coefficient is an important metric for evaluating both the performance and reliability of RFA, as it measures the contribution of each tree in the model. The higher the multiple explanatory coefficient of a feature, the more important it is; that is, the feature provides more information and has a greater impact on predictions. Additionally, the trend of the multiple explanatory coefficient with respect to the number of trees helps us understand its effect on model performance. In other words, while adding more trees can improve the overall performance of the model, the contribution of each individual tree may decrease. This can help reduce overfitting and make the model more generalizable. Furthermore, the variation of the multiple explanatory coefficient with the number of trees can also reflect the stability of the random forest model. If the multiple explanatory coefficients increase steadily with the number of trees, the model's reliability improves. However, fluctuations or decreases in the coefficients as the number of trees increases may indicate instability in the model or uncertainty about the importance of certain features in the predictions.

In the developed model, while the multiple explanatory coefficient showed a rapid change as the number of trees increased from 10 to 15, it exhibited a slower upward trend as the number of trees increased gradually from 15 to 50. The highest multiple explanatory coefficient was reached when the number of trees was 50, with a value of 0.9975. Increasing the number of trees beyond this point led to a decrease in the multiple explanatory coefficient. As a result, the number of trees in this study was determined to be 50 for the biomass consumption prediction model.

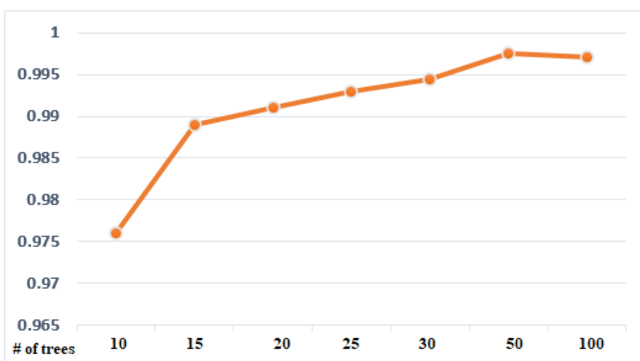


Figure 5. Variation of the Multiple Explanatory Coefficient Based on the Number of Decision Trees

5. Conclusion and Recommendations

In this study, forecasting the bioenergy potential for the near future at the European scale was carried out using ROA. The data obtained from the forecasting model provided highly accurate (R^2=0.9975) predictions of the biofuel consumption data planned for the near future. The best prediction result was achieved with a decision tree parameter set at 50 trees. The predicted biofuel consumption values for European countries in 2025, 2030, and 2050 were found to be 821,598, 1,090,569, and 1,895.46 PJ, while for Other European countries, these values were 155.722, 174.954, and 288.96 PJ for the same years. The developed model can be used to predict consumption profiles for the design of renewable biomass energy systems and their integration into existing systems.

Turkey, by evaluating its agricultural, domestic, and forest biomass resources, can replace fossil fuels with biofuels, thus reducing greenhouse gas emissions. Turkey is expected to make a significant contribution to the anticipated increase in biofuel consumption in 2030 and 2050. Turkey's biomass and biofuel potential should be supported by extensive agricultural areas, waste management, and renewable energy investments. For Turkey, which holds a strategic position for energy trade, biofuel production that can be created with efficient energy crops and integrated waste management strategies could enhance energy supply security and reduce dependence on energy imports.

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