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Research paper

Economic indicators and bioenergy supply in developed economies: QROF-DEMATEL and random forest models

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ABSTRACT

Bioenergy is a renewable energy source that saves from fossil fuel dependence. Therefore, it is important to increase the efficiency of bioenergy investments to create an environmentally sustainable energy supply. This paper aims to identify economic indicators significant in forecasting the supply of bioenergy. Considering this goal, an integrated evaluation has been performed for 17 developed economies using the Random Forest method and the Fuzzy Decision-Making Trial and Evaluation Laboratory (QROF-DEMATEL) method. The main contribution of this study is conducting analysis by using both quantitative and qualitative data. Additionally, the coherence of the results made with the QROF-DEMATEL method is also verified by implementing a sensitivity analysis. The results of both approaches are quite similar and provide information about the reliability of the findings. This situation demonstrates that for the development of bioenergy investments, firstly, countries' macroeconomic conditions should be improved. Consequently, economic growth and unemployment (weighting results - 0.159 and 0.155) should be primarily considered for the bioenergy supply forecast.

1. Introduction

One of the most important conditions for increasing the efficiency of biomass energy investments is estimating the supply. The main reason for this is that the produced energy must fully meet the country's demand (Ishaq and Dincer, 2020). In a case of under-produced biomass energy, the country's demand will not be fully met. In this case, the country will either resort to fossil resources or have to import energy from other countries. This issue harms the country both economically and environmentally. On the contrary, if more biomass energy is produced than needed, the efficiency of energy investments will decrease (Colantoni et al., 2021). As a result, it will not be possible to ensure the sustainability of biomass energy investments.

Biomass energy is a type of energy obtained by burning organic materials. The materials burned in this process are not fossil fuels. Therefore, no carbon emission occurs in the process of securing biomass energy. Consequentially, it is possible to reduce the dependence on fossil fuels by producing environmentally sustainable energy (Irfan et al., 2020). Biomass energy also has some advantages compared to other types of renewable energy. For example, biomass energy is much easier to store. This situation brings a significant cost advantage to this type of energy. Furthermore, biomass energy sources can be found in abundance in nature. This results in increased efficiency of biomass energy investments (Konuk et al., 2021; Paraschiv and Paraschiv, 2020).

There are many different factors that can affect the biomass energy production target. For example, biomass energy production may be related to the country's GDP. A developing national economy leads to increased demand for energy. In this context, it would also be beneficial to increase biomass investments in countries with more economic development (Singh et al., 2020). However, industrial production will decrease in countries experiencing an economic recession. This leads to lower energy demand. In addition, the unemployment rate in the country can also

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be taken into account for estimating biomass energy production. In a country with a high unemployment rate, both economic development and industrial production will decrease. This reduces the need for biomass energy. On the other hand, the decrease in unemployment rate gives positive signals for economic development (Muazu et al., 2020). In the conditions, it would be the right decision to increase biomass energy production (Králík et al., 2020; Rahman et al., 2021).

Moreover, the decrease in stock market indices also signals that investments in the country may decrease. In this case, reducing biomass energy production would be a good practice (Herrera et al., 2019). Regarding this process, past data of indices' variables will be taken into account and forecasts for biomass energy production can be made (Kolin et al., 2021). The most important limitation of these methods is that variables without numerical data cannot be taken into account. However, it is possible to estimate biomass energy production by considering multi-criteria decision-making techniques (Li et al., 2020; Zhao et al., 2021). In this process, the evaluations of experts who know on the subject should be considered. Due to this situation, it will be possible to determine issues that cannot be explained with numerical data, and it will be possible to use variables that do not have numerical data (Zhong et al., 2020).

This study aims to define important factors regarding the bioenergy supply forecast. Within this context, two different evaluations have been conducted for 17 developed economies. In these analyses, seven different variables are used: economic growth, unemployment rate, the industrial production index, inflation dynamics, Brent oil prices, natural gas prices and the S&P500 index (Bildirici, 2013; Bilgili and Öztürk, 2015). Firstly, an econometric analysis is performed by using the random forest ensemble method. In this process, data for the bioenergy supply forecast for the period from January 2000 to December 2018 is utilized. Secondly, another analysis has been made in line with the Fuzzy Decision-Making Trial and Evaluation Laboratory (QROF-DEMATEL) methodology. In this evaluation, both the weights of the variables and the causality relationship can be identified (An et al., 2021; Bhuiyan et al., 2021; Danish et al., 2021).

The dataset is exported from Thomson Reuters Datastream. The data consist of normalized parameters for the period from 2000 to 2018 for 17 developed countries: Austria, Great Britain, Hungary, Germany, Israel, Ireland, Spain, Italy, Canada, Norway, Portugal, USA, Finland, France, Czech Republic, Switzerland, and Sweden. This period is optimal for proposed models. The paper uses data about these 17 countries because they have the potential for biofuel revolution. All analyses of the data used was done in Python.

The use of both quantitative and qualitative data in the evaluation in this study provides an opportunity to compare results to measure the coherency of the findings. Additionally, using the random forest ensemble method creates some benefits because historical data of the numerical variables can be considered (Yadav and Pal, 2020; Xu et al., 2019). Furthermore, the use of the QROF-DEMATEL approach evaluation also provides some benefits. The rest of the paper is organized as follows: the second section consists of literature review for the bioenergy supply, the third section includes the definition of the QROF-DEMATEL methodology, the fourth section explains the results from analyses. Finally, the conclusions of the manuscript are shared.

2. Literature review

In past research, many different researchers have evaluated the relationship between biomass energy and economic growth. Biomass energy investments can contribute to economic growth in many ways. First, the country can produce its energy by using its biomass (Bildirici, 2013). This will reduce the country's dependence on foreign trade and tariffs for energy. It will be easier for a country without a current account deficit to develop economically (Adewuyi and Awodumi, 2017). Furthermore, investments in biomass energy create job opportunities for the population and raw material suppliers (Sinaga et al., 2019). This helps increase economic mobility in the country. Bilgili and Öztürk (2015) focused on the relationship between biomass energy and economic growth for G7 economies. With the help of dynamic panel data analysis, it is identified that biomass energy investments contribute significantly to economic improvements. Aydın (2019) tried to define the impact of biomass energy on the economic growth in BRICS economies. In this study, a country-specific panel data evaluation has been performed. It was concluded that for the economic development of these countries, biomass energy investments should be increased. Sarkodie et al. (2019) and Wang et al. (2020) also reached similar conclusions in their studies.

A significant number of previous studies have emphasized the importance of technological development in biomass energy investments. Many investors focus on the problem of energy storage (Shahbaz et al., 2019) in biomass energy production. However, new technologies for producing biomass energy are constantly being developed. Investors following and applying these technologies gain a significant competitive advantage (Sansaniwal et al., 2017). At the same time, investors in biomass energy can't survive in the absence of innovative technology (Yamakawa et al., 2018).

Daioglou et al. (2019) focused on biomass supply and demand. The authors highlight the significance of technological improvement to increase the efficiency of these investments. Lamb and Pollet (2020) also described the importance of new technologies for biomass investments. Mao et al. (2018) made a bibliometric analysis regarding the utilization of biomass energy and the environment. They identified that technological improvements should be followed effectively by the investors. Suzuki et al. (2017) evaluated the biomass energy potential in Malaysia and found a positive correlation between technological development and biomass energy supply.

Energy storage costs are a topic that has been discussed many times regarding biomass energy. Since it is affected by many external factors, the amount of produced energy can vary depending on different periods (Caliano et al., 2017). As a result, more energy could potentially be obtained than needed. For this energy to be utilized efficiently, the excess amount obtained must be appropriately stored (Sahoo and Mani, 2017). Consequentially, this situation negatively affects the efficiency of biomass energy investments because it creates additional costs (Timmons et al., 2020). In this context, studies are carried out to reduce the storage costs in biomass energy investments. Yuan et al. (2019) focused on evaluating different storage models for the generated biomass power. The authors highlighted that energy storage costs should be minimized to increase the efficiency of biomass energy investments. Roni et al. (2019) aimed to optimize the biomass supply chain cost. Jayarathna et al. (2020) also tried to identify the optimal ways to minimize the storage costs of biomass energy projects.

Many researchers focused on estimating the biomass energy supply. In these studies, some other variables were taken into consideration. Samadi et al. (2020) tried to predict biomass energy supply from agricultural residues in Iran. Owing to the evaluation with the robust model, it is defined that technological development is beneficial to producing better estimations. Yang et al. (2018) also underlined the significance of this situation for biomass energy supply prediction. Furthermore, Say and Yücel (2006) defined that the country's national economic growth parameters should be used to make more accurate estimations. Güney and Kantar (2020) also found a significant relationship between biomass energy consumption and economic growth. On the other side, Xiao et al. (2020) and Çepelioğullar et al. (2018) conducted an econometric analysis to predict biomass consumption by considering its historical data.

The literature review results indicate that the subject of biomass energy is gaining widespread attention. Researchers focus on all of the different aspects of this subject, such as the impact of biomass energy on economic growth, energy storage cost problems in biomass energy, and the role of technological improvements on the efficiency of the biomass projects. Some studies aim to estimate the biomass energy supply. However, most of these studies focused on econometric models by looking at only the historical data of biomass energy consumption. Hence, a comprehensive variable list should be generated to forecast biomass energy supply. Additionally, the consistency of the analysis results should also be verified using qualitative methods. In this context, the article aims to define important factors with respect to the bioenergy supply forecast. For this purpose, a detailed variable list is created consisting of economic growth parameters, unemployment rate, the industrial production index, inflation dynamics, brent oil prices, natural gas prices and the S&P500 index. Moreover, a comparative evaluation is conducted by considering both the random forest ensemble method and the QROF-DEMATEL methodology.

The advantages of the presented methodology are in relation to Bilgili and Öztürk (2015), which focused on the relationship between biomass energy and economic growth for G7 countries. This paper uses more accurate methods and extends the list of countries to 17 developed markets. The advantages of the presented methodology in relation to Samadi et al. (2020) and Yang et al. (2018) are: more prudent international analysis and the implementation of the QROF-DEMATEL methodology.

3. QROF-DEMATEL

3.1. Q-Rung orthopair fuzzy sets

With the help of expert opinions, non-numerical factors can also be taken into consideration in addition to the numerical ones. Therefore, a detailed variable list can be generated. Moreover, this methodology helps to identify the causality relationship between the variables (Dinçer and Yüksel, 2018; Zhang et al., 2020; Jun et al., 2021).

Furthermore, using fuzzy logic with the MCDM method is very helpful to handle uncertainty more efficiently. On the other side, by considering QROF sets, a wider space for information representation can be provided (Garg, 2021; Peng and Liu, 2019). This situation contributes to more freedom of the expertes' opinions (Garg and Chen, 2020; Dinçer and Yüksel, 2018). Additionally, the coherence of the analysis results made by the QROF-DEMATEL model is also verified using the sensitivity analysis. Therefore, the reliability of the findings can be examined as well. The analysis results of this study pave the way for investors and policy makers. With the help of the article's findings, more appropriate estimations can be made for the bioenergy supply. This situation contributes to the efficiency of investments in environmentally-friendly energy generation. Intuitionistic fuzzy sets (I) include more comprehensive evaluations for the decision-making process. Eq. (1) gives information about this process (Alcantud et al., 2020).

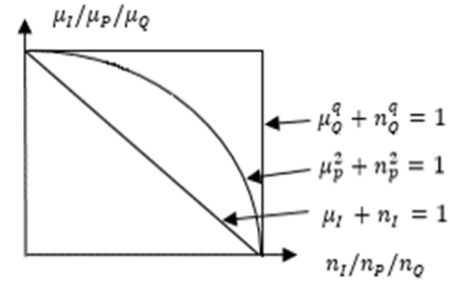

Fig. 1. Membership and non-membership degrees of IFS, PFS, and q-ROFSs.

$$I = \{\langle \vartheta, \mu_I(\vartheta), n_I(\vartheta)\rangle /\vartheta \epsilon U\} \quad (1)$$

Where $\mu_I(\vartheta): U \rightarrow [0,1]$ represents membership degrees, whereas the non-membership parameter is given as $n_I(\vartheta): U \rightarrow [0,1]$. Additionally, the condition of $0 \le \mu_I(\vartheta) + n_I(\vartheta) \le 1$ should be satisfied. The degrees of belongingness and non-belongingness are shown as $\mu_I(\vartheta)$ and $n_I(\vartheta)$ (Garg and Rani, 2019; Song et al., 2019).

Pythagorean fuzzy sets indicate new fuzzy membership grades to give a more appropriate solution for decision-making problems. Eq. (2) demonstrates the details of these sets (Zhou et al., 2020).

$$P = \{\langle \vartheta, \mu_P(\vartheta), n_P(\vartheta)\rangle /\vartheta \epsilon U\} \quad (2)$$

Additionally, the condition stated in Eq. (3) should be met (Ak and Gul, 2019).

$$0 \le (\mu_P(\vartheta))^2 + (n_P(\vartheta))^2 \le 1 \quad (3)$$

Q-rung orthopair fuzzy sets (q-ROFSs) are an extension of these two different fuzzy sets. q-ROFSs aim to solve more complex problems. The main advantage of these sets is the ability to consider a larger membership grade space. Eq. (4) indicates these fuzzy sets (Ali and Mahmood, 2020).

$$Q = \left\{\left\langle \vartheta, \mu_Q(\vartheta), n_Q(\vartheta)\right\rangle /\vartheta \epsilon U\right\} \quad (4)$$

The condition of q-ROFSs is shown in Eq. (5) (Garg, 2021).

$$0 \le \left(\mu_Q(\vartheta)\right)^q + \left(n_Q(\vartheta)\right)^q \le 1,\ q \ge 1 \quad (5)$$

Also, Fig. 1 demonstrates the differences of these three fuzzy sets (Peng and Liu, 2019).

Eq. (6) includes the degree of indeterminacy (Garg and Chen, 2020).

$$\pi_Q(\vartheta) = \left(\left(\mu_Q(\vartheta)\right)^q + \left(n_Q(\vartheta)\right)^q - \left(\mu_Q(\vartheta)\right)^q \left(n_Q(\vartheta)\right)^q\right)^{1/q} \quad (6)$$

On the other side, Eqs. (7)–(11) include the mathematical details of q-ROFSs (Lin et al., 2020).

$$Q_1 = \left\{\left\langle \vartheta, Q_1(\mu_{Q_1}(\vartheta), n_{Q_1}(\vartheta))\right\rangle /\vartheta \epsilon U\right\} \text{ and } Q_2 = \left\{\left\langle \vartheta, Q_2(\mu_{Q_2}(\vartheta), n_{Q_2}(\vartheta))\right\rangle /\vartheta \epsilon U\right\} \quad (7)$$

$$Q_1 \oplus Q_2 = \left(\left(\mu_{Q_1}^q + \mu_{Q_2}^q - \mu_{Q_1}^q \mu_{Q_2}^q\right)^{1/q}, n_{Q_1} n_{Q_2}\right) \quad (8)$$

$$Q_1 \otimes Q_2 = \left(\mu_{Q_1}\mu_{Q_2}, \left(n_{Q_1}^q + n_{Q_2}^q - n_{Q_1}^q n_{Q_2}^q\right)^{1/q}\right) \quad (9)$$

$$\lambda Q = \left(\left(1-\left(1-\mu_Q^q\right)^\lambda\right)^{1/q}, \left(n_Q\right)^\lambda\right), \lambda > 0 \tag{10}$$

$$Q^\lambda = \left(\left(\mu_Q\right)^\lambda, \left(1-\left(1-n_Q^q\right)^\lambda\right)^{1/q}\right), \lambda > 0 \tag{11}$$

Score function is used for the defuzzification process as in Eq. (12) (Ali and Mahmood, 2020).

$$S(\vartheta) = \left(\mu_Q(\vartheta)\right)^q - \left(n_Q(\vartheta)\right)^q \tag{12}$$

3.2. DEMATEL

DEMATEL is used to find more significant factors among many different alternatives. Additionally, the causality analysis can also be performed due to the impact relation map. Firstly, the decision matrix (A) is created as in Eq. (13) (Yuan et al., 2021).

$$A = \begin{bmatrix} 0 & a_{12} & a_{13} & & \cdots & a_{1n} \\ a_{21} & 0 & a_{23} & & \cdots & a_{2n} \\ a_{31} & a_{32} & 0 & & \cdots & a_{3n} \\ \vdots & \vdots & \vdots & \ddots & & \vdots \\ a_{n1} & a_{n2} & a_{n3} & & \cdots & 0 \end{bmatrix}. \tag{13}$$

Secondly, the normalized matrix (B) is created by Eqs. (14) and (15) (Haiyun et al., 2021).

$$B = \frac{A}{max_{1\le i\le n}\sum_{j=1}^{n} a_{ij}}, \tag{14}$$

$$0 \le b_{ij} \le 1. \tag{15}$$

Thirdly, the total relation matrix (C) is generated by Eq. (16) (Delen et al., 2020).

$$\lim_{k\to\infty}\left(B + B^2 + \cdots + B^k\right) = B(I-B)^{-1}. \tag{16}$$

Fourthly, the sums of rows and columns (D, E) are computed with Eqs. (17) and (18). The sum of these values are used to find the weights while the causal relationship is defined by the differences of these values (Dinçer and Yüksel, 2018).

$$D = \left[\sum_{j=1}^{n} e_{ij}\right]_{nx1}, \tag{17}$$

$$E = \left[\sum_{i=1}^{n} e_{ij}\right]_{1xn}. \tag{18}$$

Finally, the threshold value (α) is calculated to make causal relationship as in Eq. (19) (Zhang et al., 2020).

$$\alpha = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}\left[e_{ij}\right]}{N}. \tag{19}$$

4. Application

This section initially introduces the background of the analyses. After that, comparative results are presented.

4.1. Analysis background

Seven variables are used: economic growth, unemployment rate, the industrial production index, inflation dynamics, Brent oil prices, natural gas prices, and the S&P500 index. The dataset is exported from Thomson Reuters Datastream. The data consist of normalized parameters for the period from 2000 to 2018 for 17 developed countries: Austria, Great Britain, Hungary, Germany, Israel, Ireland, Spain, Italy, Canada, Norway, Portugal, USA, Finland, France, Czech Republic, Switzerland, and Sweden. This period is optimal for proposed models. The paper uses data about these 17 countries because they have the best opportunities for biofuel revolution. The article analyses all of the data in Python. After this, new parameters are generated:

standard error for biofuel supply;
model factors' significance level;
the mean absolute error model for all factors.

For modeling, data on GDP, inflation, industrial index, and unemployment (all variables by type features and test data) were utilized. The values that the model aims to predict are used as the target vector.

As with any regression analysis, the unknown function of the estimation is expressed by the following formula (Abuella and Chowdhury, 2017):

$$\mathrm{Y} = \mathrm{f}(\mathrm{X}, \beta) + e_i \tag{20}$$

where Y is the range of dependent variables; X is the independent variable. β and e_i represent unknown parameters and the error terms, respectively. General view of the linear model is as follows (Yadav and Pal, 2020):

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \hat{\beta} x_2 + \hat{\beta}_3 x_3 + \hat{\beta}_4 x_y + \varepsilon \tag{21}$$

$$\text{Biomass supply} = 1.73^*\text{EG} - .35^*\text{U} + .12^*\text{IPI} - .012^*\text{I} \tag{22}$$

where EG is economic growth, U is the unemployment rate, IPI is the industrial production index and I is inflation dynamics.

General view of the polynomial model (Xu et al., 2019):

$$\hat{y} = \hat{\beta} + \hat{\beta}_1 x_1 + \hat{\beta}_2 x_1^2 + \cdots + \hat{\beta}_d x_l^d + \varepsilon \tag{23}$$

This follows from the linear function for each attribute (Abuella and Chowdhury, 2017):

$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 x_1 + \varepsilon \tag{24}$$

All data was preprocessed before starting the simulation. The increments reduction method is as follows:

$$\mathrm{xn} = (\mathrm{xn} - \bar{x})/\sigma \tag{25}$$

The "size" attribute is obtained and sorted to three groups of observation data (25%) and the rest of the sample (75%). The "shape" attribute also outperformed three groups of observations (25%) and the remainder of the sample (50%). The "color" attribute determined the rest of the sample; that is, it was significant for 50% of the observations. The importance of the main features is at a level of .25; .25; .5, which is relatively significant (Fig. 2).

The paper combines a lab scale analysis with factor analysis. For the manufacturing of pellets, different combinations of the biomass were made to identify the mixture that produces better quality pellets (Mao et al., 2018; Muazu et al., 2020). The calorific value is the most important parameter to specify a substance as fuel. The calorific value of biomass is defined as the amount of energy released in the form of heat when it burns completely. The pellets are manufactured using pure honey as a binder similar to other investigations, this binder was used to facilitate compaction and adhesion with the used biomasses. Pellets made with a composition of 40% rice husk, 30% coconut, 20% wood sawdust, and 10% binder presented a calorific value of around 7.685 (MJ/kg).

Pellet moisture content is very important from the point of view of energy use, it is the one that has the most influence on the calorific value of biofuels, along with the kind that waste belongs to. The percentage of moisture content is calculated as follows: a pellet of each composition, the tray is prepared with the reference sample in the oven at 105 ºC for 24 h. The moisture content calculation is performed (26) (Paraschiv and Paraschiv,

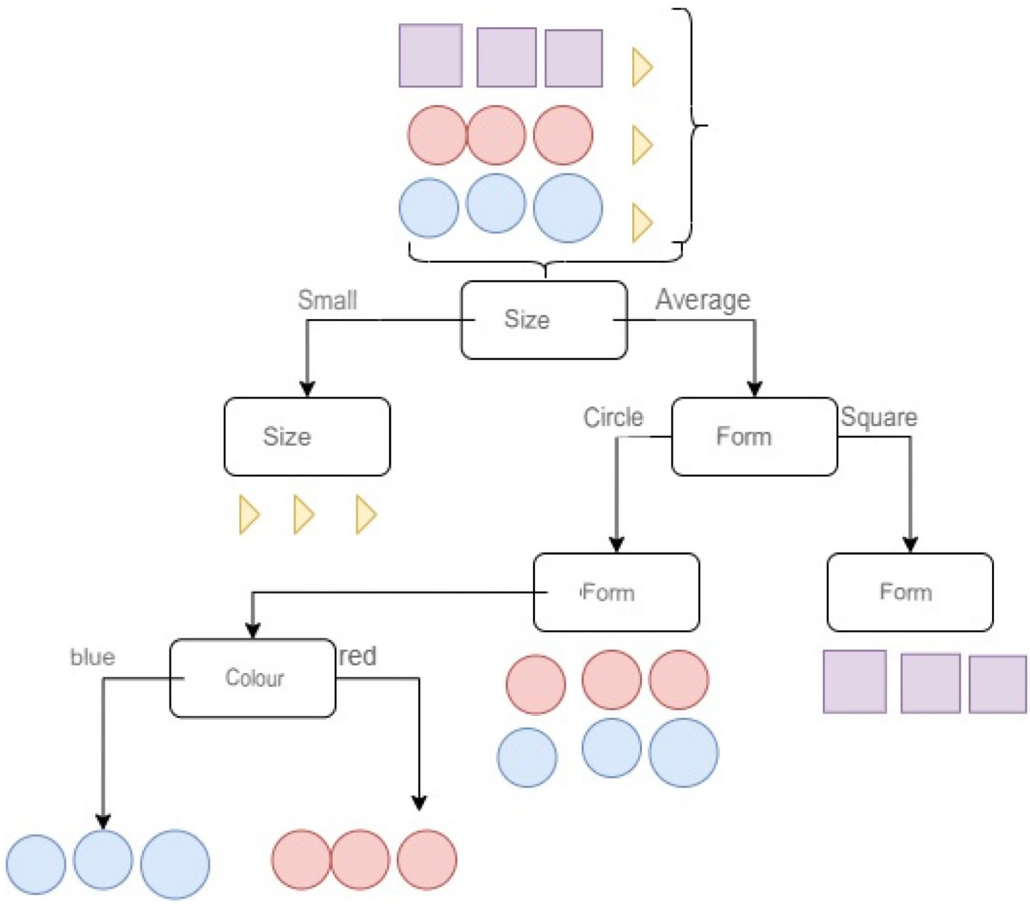

Fig. 2. Model classification based on composition of size (M1), form (M2) and color (M3) samples.
Source: Authors.

2020; Peng and Liu, 2019; Rahman et al., 2021; Roni et al., 2019; Saad and Taleb, 2018).

$$\text{Moisture content} = (\text{M-F})/\text{M} \tag{26}$$

where M is the mass of the biomass in the beginning, F is the mass of the biomass at the end.

The calorific value is the amount of energy released in the conditions of a chemical reaction of oxidation.

The moisture content effect on the calorific value of the studied resources was calculated based on the heat of combustion determined by the calorimetric method using a KL-12Mn type calorimeter. In summary, the technique consists of burning approximately 1 gram of material to analyze it in a calorimetric pump with an oxygen atmosphere at an initial pressure. The combustion reactor is inside a calorimeter, and the temperature changes when combustion is performed. This results in released heat during combustion (Sahoo and Mani, 2017; Samadi et al., 2020; Sansaniwal et al., 2017).

Superior calorific value (PCS) is the total amount of heat given off in combustion complete of 1 kg of fuel when the water vapor originated by the combustion is condensed. Consequently, the heat given off in this phase change is counted.

The lower calorific value (PCI) is the total amount of heat given off in a complete combustion of 1 kg of fuel without counting the part corresponding to the latent heat of the steam combustion water since no phase change occurs, and it is expelled as steam.

4.2. Comparative results

This section first presents the results of the random forest ensemble model. After that, the QROF-DEMATEL analysis results are shared.

4.2.1. Results with random forest ensemble model

Moisture plays an important role in pelletized biomasses because it is a factor that affects the ease of compacting the raw material, the density, stability, and durability of the pellets. This is because of the following conditions: if the pellets have a high percentage moisture content, their transport and storage will be difficult and their combustion will be very slow, and negative at the time of being used. Several researchers have recommended a lower moisture content than 10% for forming pellets of different materials. However, in some research, good-quality pellets were obtained with 11% and 18% moisture content, indicating that adequate moisture content depends on the type of residue (Fig. 3).

Relatively high densities were obtained with the pellet processing parameters of minimal variation, indicating good compaction regarding the bulk density of the pellets. Low density negatively affects energy density and, therefore, the costs of transport and storage capacity for both the producer and the end-user of pellets. Mixtures were chosen to make the pellets present good compaction.

The content of volatile matter is of great importance in the combustion rate, since a high value indicates that some biomass materials are released quickly, producing a decrease in their mass

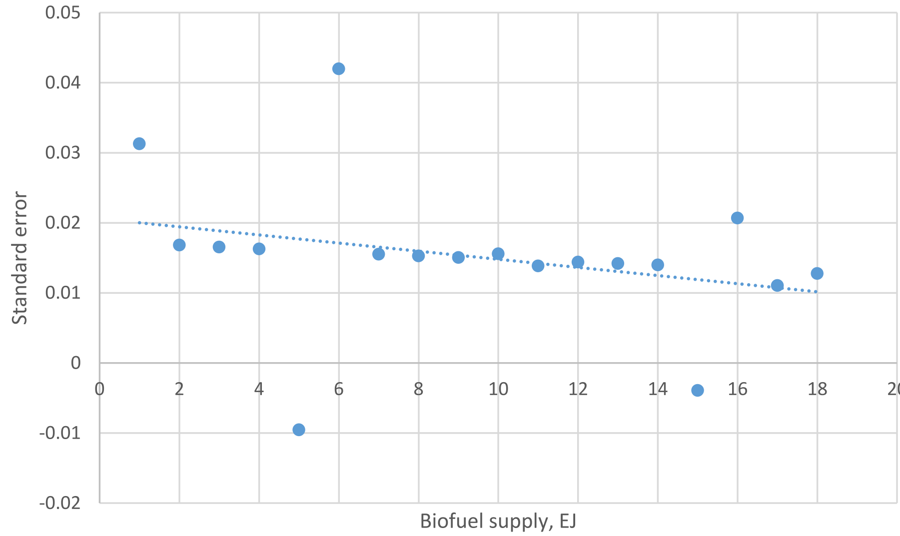

Fig. 3. Standard error of biofuel supply factor analysis.

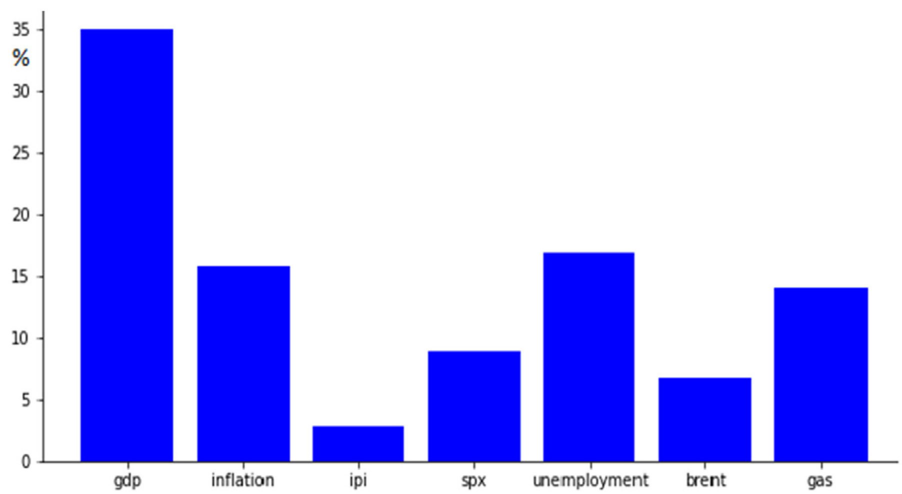

Fig. 4. Model significance levels.

and facilitating combustion. Additionally, it generates a smaller amount of unburned (soot), and complete combustion would be expected.

All three types of pellets presented high volatile material content, demonstrating that biomasses have suitable characteristics for easy combustion. The durability of the pellets is a very important variable for their conservation and handling. This variable depends on the degree of compaction and attraction of the biomass components (Fig. 4).

Recent studies have found that the demand for biofuels can cause two groups of effects: economic effects and food security effects. The development of the economy is determined by the market. The results of this study support this thesis. Since the raw materials for producing biofuels are the same natural resources, there are constant discussions concerning the positive and negative impact of biofuels on the food sector's development (Güney and Kantar, 2020; Haiyun et al., 2021; Herrera et al., 2019). Usually, the first 20 epochs are useless for validation. The random forest model is retrained due to the small size of the dataset after 100 epochs, so the significant modeling interval is chosen [20; 100] (Figs. 5–6).

The effect of moisture content on economic growth is shown (Table 1). For the rice husk and sawdust of wood, the value is

Table 1
Moisture content effect on the calorific value.

Direction of effect	Random forest model forecast (%)
Calorific value growth	.713 ±.117
Calorific value decline	.447 ±.106

*Error terms reflect the 95% confidence intervals.

4.850 (MJ/kg), for rice husk to coconut value is 4.206 (MJ/kg). The sulfur contained in fuels is associated with environmental contamination of the energy generation. Although its sulfur content was not measured in the context of this article, it is well known that the plant biomass has a low enough content to consider it insignificant.

4.2.2. *Results with QROF-DEMATEL*

The expert team considers the linguistic evaluations for the criteria by using the scales in Table 2.

On the other side, linguistic evaluations of the expert team are shared in Table 3.

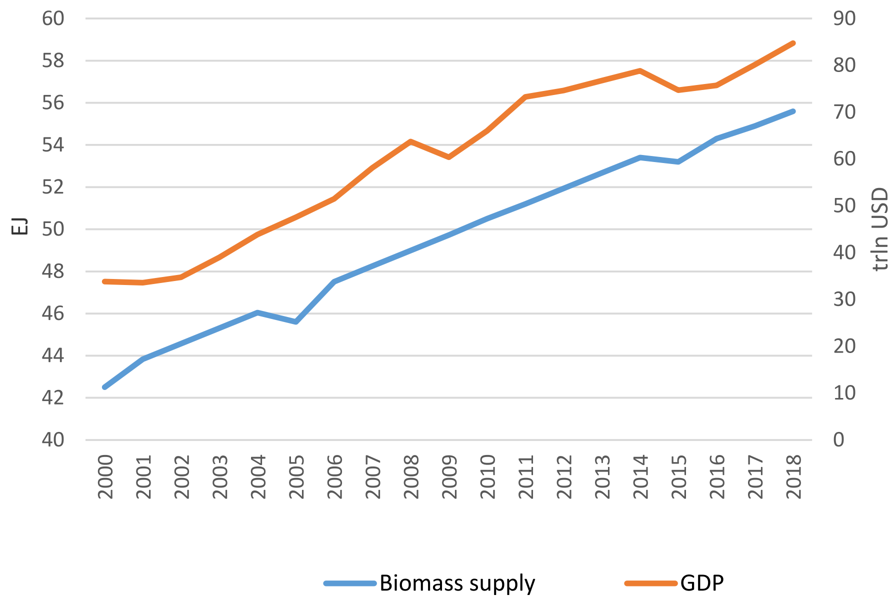

Fig. 5. Biomass supply.
Source: Thomson Reuters Datastream.

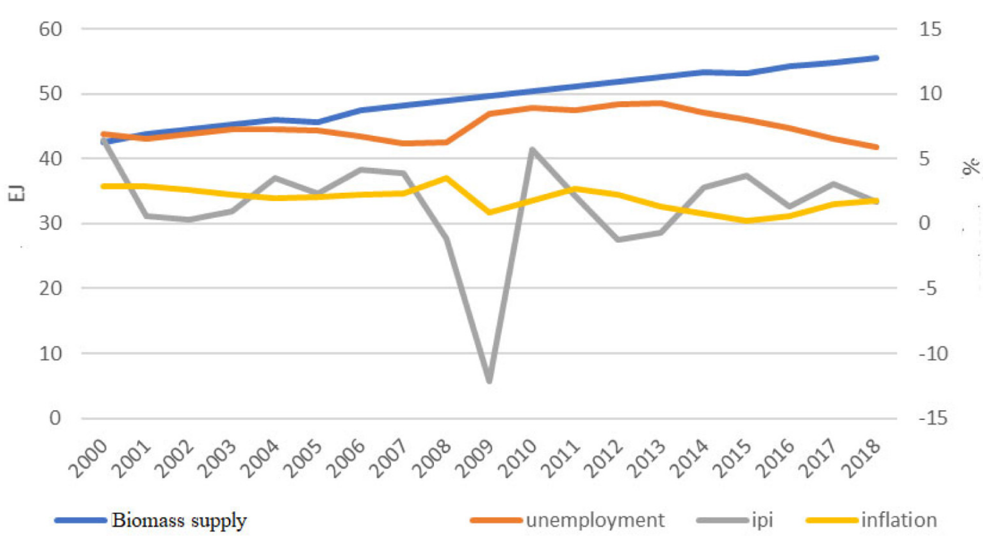

Fig. 6. Biomass supply.
Source: Thomson Reuters Datastream.

Table 2
Linguistic scales, membership and non-membership degrees for criteria.

Linguistic scales for criteria	Membership degrees	Non-membership degrees
No influence (n)	.10	.90
somewhat influence (s)	.30	.70
medium influence (m)	.60	.40
high influence (h)	.80	.20
very high influence (vh)	.90	.10

Moreover, membership and non-membership degrees are calculated for the criteria in Table 4.

Furthermore, the score function values of the criteria for Q-ROF sets are shown in Table 5.

Later, these values are normalized as in Table 6.

Next, total relation matrix is developed as in Table 7.

Finally, the weight results are computed as in Table 8.

Table 8 indicates that GDP (weighting results - 0.159) is the most significant factor for bioenergy supply prediction. In addition, unemployment is also another important item in this regard (weighting results - 0.155). On the other side, IPI and SPX have lower weights when compared to other factors. Furthermore, sensitivity analysis has also been performed by considering 12 different Q values. The results are shared in Table 9.

Table 9 gives information that analysis results are quite similar for different Q values. This situation indicates that the findings of this manuscript are reliable. Moreover, by considering "D-E" values in Table 9, the impact-relation map is created for the items as in Fig. 7.

Fig. 7 gives information that brent is the most influencing factor. On the other side, inflation and unemployment are the most influenced criteria.

Table 3
Linguistic evaluations.

Variables	C1 (IPI)	C2 (GDP)	C3 (Brent)	C4 (Inflation)	C5 (Unemployment)	C6 (SPX)	C7 (Gas)
C1 (IPI)		S	M	H	VH	M	H
C2 (GDP)	M		H	H	H	VH	H
C3 (Brent)	H	H		H	H	H	M
C4 (Inflation)	M	M	S		M	M	H
C5 (Unemployment)	M	H	M	VH		M	M
C6 (SPX)	M	M	H	VH	H		M
C7 (Gas)	M	H	M	H	VH	H	

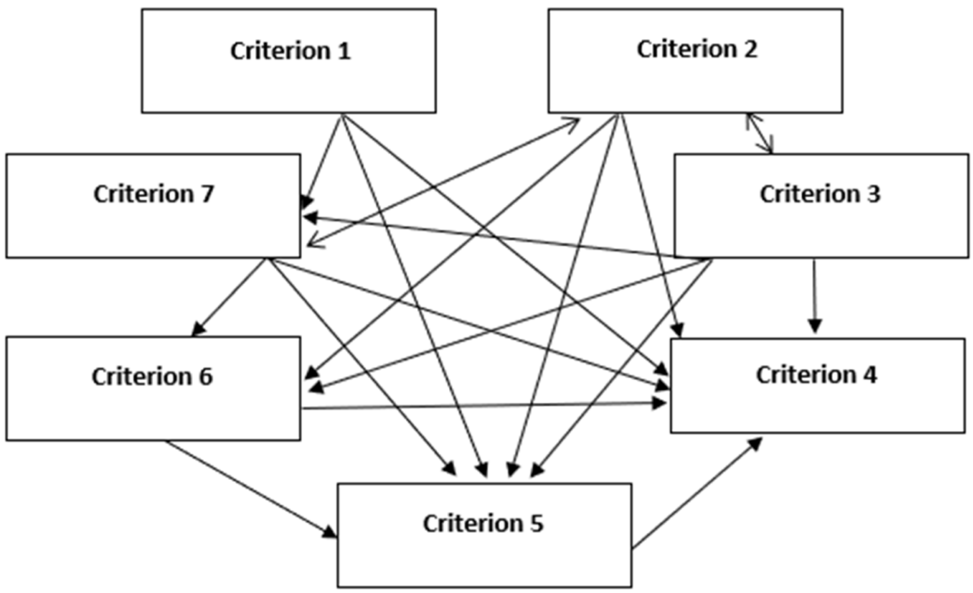

Fig. 7. Impact-relation map of the criteria.

Table 4
Membership and non-membership degrees for the criteria.

	C1		C2		C3		C4		C5		C6		C7	
	μ	v	μ	v	μ	v	μ	v	μ	v	μ	v	μ	v
C1			.30	.70	.60	.40	.80	.20	.90	.10	.60	.40	.80	.20
C2	.60	.40			.80	.20	.80	.20	.80	.20	.90	.10	.80	.20
C3	.80	.20	.80	.20			.80	.20	.80	.20	.80	.20	.60	.40
C4	.60	.40	.60	.40	.30	.70			.60	.40	.60	.40	.80	.20
C5	.60	.40	.80	.20	.60	.40	.90	.10			.60	.40	.60	.40
C6	.60	.40	.60	.40	.80	.20	.90	.10	.80	.20			.60	.40
C7	.60	.40	.80	.20	.60	.40	.80	.20	.90	.10	.80	.20		

Table 5
Score function values of the criteria for q-ROFs.

	C1	C2	C3	C4	C5	C6	C7
C1	.000	−.316	.152	.504	.728	.152	.504
C2	.152	.000	.504	.504	.504	.728	.504
C3	.504	.504	.000	.504	.504	.504	.152
C4	.152	.152	−.316	.000	.152	.152	.504
C5	.152	.504	.152	.728	.000	.152	.152
C6	.152	.152	.504	.728	.504	.000	.152
C7	.152	.504	.152	.504	.728	.504	.000

Table 6
Normalized DRM.

	C1	C2	C3	C4	C5	C6	C7
C1	.000	.000	.052	.174	.251	.052	.174
C2	.052	.000	.174	.174	.174	.251	.174
C3	.174	.174	.000	.174	.174	.174	.052
C4	.052	.052	.000	.000	.052	.052	.174
C5	.052	.174	.052	.251	.000	.052	.052
C6	.052	.052	.174	.251	.174	.000	.052
C7	.052	.174	.052	.174	.251	.174	.000

Table 7
Total DRM.

	C1	C2	C3	C4	C5	C6	C7
C1	.139	.239	.198	.547	.537	.279	.388
C2	.269	.336	.407	.741	.635	.579	.494
C3	.349	.444	.230	.687	.593	.477	.378
C4	.135	.194	.107	.247	.264	.207	.305
C5	.182	.356	.204	.576	.295	.283	.287
C6	.212	.294	.322	.636	.489	.254	.307
C7	.231	.443	.272	.666	.626	.466	.305

These results demonstrate that for the development of bioenergy investments, firstly, the countries' macroeconomic conditions should be improved. Therefore, economic growth and unemployment rate problems should be primarily taken into consideration for the forecast of the bioenergy supply. There is a positive relationship between economic development and bioenergy supply. Therefore, the countries that have high economic development will need more bioenergy. The main reason is that in these countries, industrial production will increase. Because energy is accepted as the main input resource of industrial production, the country should obtain more energy for this situation. Saad and Taleb (2018) and Wang et al. (2020) also determined that economic growth significantly influences the biomass energy supply. Furthermore, the unemployment rate in the country should also be considered for the biomass energy production estimation. In the case of a high unemployment rate, both economic development and industrial production may decrease,

Table 8
Weighting results with QROF-DEMATEL.

Factors	D	E	D+E	D-E	Weighting results
C1 (IPI)	2.328	1.519	3.847	.809	.106
C2 (GDP)	3.461	2.306	5.767	1.155	.159
C3 (Brent)	3.159	1.739	4.898	1.420	.135
C4 (Inflation)	1.458	4.100	5.558	−2.642	.153
C5 (Unemployment)	2.182	3.440	5.623	−1.258	.155
C6 (SPX)	2.515	2.544	5.058	−.029	.140
C7 (Gas)	3.009	2.464	5.473	.545	.151

Table 9
Sensitivity analysis of the weighting priorities.

Q values/Criteria	Q values											
	1	2	3	4	5	6	7	8	9	10	15	20
C1	7	7	7	7	7	7	7	7	7	7	7	7
C2	1	1	1	1	1	1	1	1	1	1	1	1
C3	6	6	6	6	6	6	6	6	6	6	6	6
C4	4	4	3	3	3	3	3	3	3	2	2	2
C5	2	2	2	2	2	2	2	2	2	3	3	3
C6	5	5	5	5	5	5	5	5	5	5	5	5
C7	3	3	4	4	4	4	4	4	4	4	4	4

reducing the need for biomass energy. On the contrary, the decrease in the unemployment rate gives positive signals for economic development so that biomass energy production should be increased.

In the first part of the analysis, an econometric evaluation is performed using the random forest ensemble method. In the second part of the analysis, an evaluation is conducted with the QROF-DEMATEL methodology to weigh the items and identify a causal relationship. Additionally, the coherence of the analysis results made by QROF-DEMATEL is also verified using sensitivity analysis. The results of both approaches are quite similar and provide information about the reliability of the findings. The results indicate that economic growth and unemployment (weighting results - 0.159 and 0.155) should be primarily considered for the bioenergy supply forecast. On the other side, IPI and SPX have lower weights when compared with other factors. It is also identified that brent is the most influencing factor. At the same time, inflation and unemployment are the most influenced criteria.

5. Conclusions

This study proves that fossil fuels create carbon emission problems which have a lasting negative effect on the environment. One of the renewable energy alternatives is bioenergy, which reduces fossil fuel dependence. Thus, the efficiency of bioenergy investments should be obtained for an environmentally sustainable energy supply. The article aims to define important factors with respect to the bioenergy supply forecast. Regarding this goal, two different estimates have been provided for 17 developed economies. Moreover, with the help of reviewed literature, seven different variables are used in the analysis: economic growth, unemployment rate, industrial production index, inflation dynamics, brent oil prices, natural gas prices, and the S&P500 index. The results prove the ideas of previous researchers in renewable energy (Bildirici, 2013; Bilgili and Öztürk, 2015). The findings indicate that economic growth and unemployment (weighting results - 0.159 and 0.155) are important for development of biofuel.

The main contribution of this study is conducting evaluation using both quantitative and qualitative data. The main limitation of this study is the consideration of only numerical values in the econometric analysis. For example, consumer behavior and the country's energy policies are also factors to be considered in energy production. Therefore, in a new future study, a comprehensive analysis can be made in which both numerical and non-numerical data are taken into account. Additionally, only developed countries are evaluated. Developing countries can also be considered for biomass energy supply prediction. On the other hand, different fuzzy numbers can also be used for subsequent studies, such as Spherical and Pythagorean fuzzy sets.

CRediT authorship contribution statement

Miraj Ahmed Bhuiyan: Conceptualization, Methodology, Software. **Hasan Dinçer:** Conceptualization, Methodology, Software. **Serhat Yüksel:** Conceptualization, Methodology, Software. **Alexey Mikhaylov:** Data curation, Writing – original draft, Visualization, Investigation. **Mir Sayed Shah Danish:** Data curation, Writing – original draft, Visualization, Investigation. **Gabor Pinter:** Software, Writing – review & editing. **Daniel Dooyum Uyeh:** Software, Writing – review & editing. **Diana Stepanova:** Software, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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