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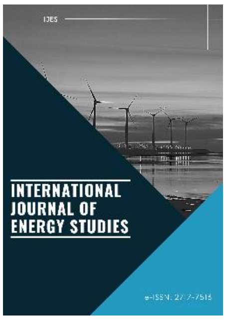

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Machine learning-based prediction of biomass energy potential from agricultural residues in Algeria

Mohamedeltayib Omer Salih EISSA[a*], Yeşim Benal ÖZTEKIN[b], Omsalma Alsadig Adam GADALLA[c], Geofrey Prudence BAITU[d], Khaled Adil Dawood IDRESS[e]

[a]*Department of Agricultural Engineering, Faculty of Engineering, University of Bahri, Khartoum Bahri, SUDAN, ORCID: 0000-0003-0186-1112*

[b]*Department of Agricultural Machinery and Technologies Engineering, Faculty of Agriculture, Ondokuz Mayis University, Samsun, TURKEY, ORCID: 0000-0003-2387-2322*

[c]*Department of Agricultural Engineering, Faculty of Agriculture, University of Khartoum, SUDAN, ORCID: 0000-0001-6132-4672*

[d]*Department of Agricultural Engineering, Faculty of Agriculture and Food Technology, University of Dar es Salaam, Dar es Salaam, TANZANIA, ORCID: 0000-0002-3243-3252*

[e]*Department of Agricultural Engineering, Faculty of Agriculture, University of Al-Neelain, SUDAN, ORCID: 0000-0002-3243-3252*

(*Corresponding Author: mohammeddl123@gmail.com)

Highlights

- Developed a ML framework to predict biomass energy potential from common agricultural residues in Algeria.
- Determination of energy potential and calorific values of diverse agricultural by-products.
- Demonstrated ML as an effective rapid-assessment tool for bioenergy resource estimation.

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ABSTRACT

The aim of this study was to assess and predict the biomass energy potential derived from agricultural residues in Algeria. Biomass energy generation from agricultural production in Algeria holds significant potential due to the country's vast agricultural resources. Algeria has diverse agricultural activities ranging from cereal cultivation to olive farming, offering various biomass feedstocks for energy production. Given the country's significant agricultural activities, residues such as straw, stalks, and husks from crops like wheat, barley, maize, and potatoes represent a valuable source of bioenergy. Production data for the 2022 growing season were obtained from the FAOSTAT database, and residue quantities were calculated using residue-to-product ratios (RPR) and calorific values. The total amount of agricultural waste was estimated at approximately 15.3 kilotons, corresponding to an energy potential of around 279 terajoules (TJ). To enhance the predictive capacity of this assessment, a machine learning approach was employed using a Random Forest Regressor. The model was trained using crop-specific features such as production volume, RPR, availability, and lower heating value (LHV) to estimate the energy potential of residues. While the model showed a strong ability to capture energy potential trends, evaluation metrics indicated room for optimization ($R^2 = -19693.04$, RMSE = 19,438.57 GJ, MAE = 17,149.01 GJ), likely due to limited dataset size. Nevertheless, the integration of ML demonstrates the feasibility of applying data-driven models to estimate biomass energy from agricultural residues and supports future planning and development of renewable energy strategies in Algeria.

Keywords: Agriculture, Renewable energy, Energy prediction, Random forest, Algeria

1. INTRODUCTION

Algeria, positioned in both Africa and the Mediterranean region, occupies a central location in North Africa, spanning latitudes between 38 and 351 degrees north and longitudes between 8 and 121 degrees east. Its landmass covers an extensive area of approximately 2,381,741 km^2[1]. Algeria shares its borders with seven countries: Mauritania, Morocco, and Western Sahara to the west; Tunisia and Libya to the east; Mali to the southwest; and Niger to the southeast [2]. Algeria occupies a strategic geographical position at the heart of North Africa, bordered by Morocco and Tunisia. Situated just 240 kilometers away from Spain and Italy across the Mediterranean Sea, its location positions it as a crucial link between Africa and Europe [3].

In recent decades, significant environmental challenges have arisen worldwide, notably concerning carbon dioxide CO_2 emissions attributable to human activities. These include the combustion of fossil fuels for energy generation and transport, deforestation, and industrial activities. These emissions have been pinpointed as primary drivers of greenhouse gas accumulation, leading to climate change and the phenomenon of global warming [4]. Global electricity production predominantly relies on fossil fuels and conventional energy sources. Nonetheless, economic, political, and environmental disruptions are increasingly posing challenges to countries worldwide [5]. The utilization of nonrenewable energy sources, such as fossil fuels, leads to the emission of greenhouse gases, which are recognized as the primary contributors to climate change. Consequently, the release of carbon emissions and the resulting global warming underscore the importance of exploring alternative energy sources [6].

Algeria, ranking among Africa's top three energy consumers and CO_2 emitters, faces the dual challenge of curbing its carbon emissions while fulfilling the energy demands of its expanding population [4]. In Algeria, despite concerted government initiatives aimed at extending electricity coverage across the nation, numerous regions still remain without access to electricity, resulting in their isolation from the power grid [5]. Algeria plays a crucial role as a prominent energy producer within Africa, with electricity generation being a pivotal aspect of its energy industry. The nation is actively engaged in enhancing its electricity sector to cater to its increasing energy needs and to foster economic diversification [3].

The escalating demand for energy resources has remained a paramount challenge for humanity. A key factor driving the surge in global energy consumption is the ongoing growth of the world's population. Presently, approximately 80% of the energy demand is fulfilled through nonrenewable fuel sources, as indicated by a statistical study conducted by [7]. Algeria, as the largest country in Africa, has witnessed a substantial surge in energy demand over the last decade, driven by notable growth in the residential, commercial, and industrial sectors [8].

Algeria's energy production relies heavily on hydrocarbons, namely oil and natural gas, which make up 93.6% of its exports. Around 90% of the country's electricity is generated primarily from natural gas power plants [9]. Numerous researchers, institutions, companies, stakeholders, and policymakers are now focusing their efforts on cleaner and more sustainable energy production and utilization methods. This shift has given rise to various trends in the energy sector, such as a transition towards renewable sources of energy instead of relying predominantly on fossil fuels [10]. African nations are actively investing in their power sectors to improve energy accessibility and promote environmental sustainability [11]. Renewable energy sources are those that can naturally replenish themselves at a rate comparable to or faster than the rate at which they are consumed. They are also characterized as durable resources that are abundantly available in nature [12]. Renewable energy sources like wind and solar power effectively decrease the carbon footprint of energy generation. Solar photovoltaic, biomass, and geothermal sources exhibit comparatively higher emissions compared to other renewables. Conversely, hydropower, marine energy, and wind power boast significantly lower emissions, contributing to cleaner energy production [13]. Renewable energy plays a crucial role in fostering sustainable economic and social progress, particularly in alleviating poverty and addressing the shift towards more sustainable production and consumption practices. Moreover, it is closely linked to the preservation and stewardship of resources in the pursuit of sustainable development. Notably, renewable energy contributes significantly to various economic objectives, with environmental preservation being paramount among them. This recognition has spurred numerous countries to prioritize the development of renewable energy sources [14].

Algeria's Renewable Energy and Energy Efficiency Development Plan prioritize the implementation of large-scale solar and wind generation projects, alongside investments in geothermal and biomass technologies [8]. Renewable sources are inexhaustible, emit no greenhouse gases, and are accessible to all, regardless of political or geographical boundaries. These sectors are poised to propel sustainable economic development, ushering in a fresh paradigm of economic growth [15]. Their universal availability fosters new industries, stimulates national economies, generates employment opportunities, delivers cost-effective energy solutions, and concurrently mitigates the negative impacts associated with conventional energy sources [2].

Biomass, which includes wood-fuel, agricultural residues, and animal waste, serves as a crucial source of fuel [16]. For millennia, mankind has relied on biomass as a primary energy source. However, following the oil crisis of the 1970s, there was a significant surge in interest in utilizing this resource in modern energy conversion facilities [17]. The primary challenges in utilizing biomass for energy production include the logistics of collection and transportation, as well as seasonal availability. These factors can lead to wide variability in biomass supply, making it unreliable for energy applications. Overcoming these barriers becomes essential for the effective utilization of biomass for energy [18].

Machine learning (ML) is increasingly used to improve the calculation and prediction of biomass energy outputs, addressing the complexity and variability of biomass materials and conversion processes. Traditional experimental and mathematical modeling approaches are often time-consuming, expensive, and limited in accuracy, making ML a valuable tool for optimizing biomass energy systems. Machine learning is applied to predict energy prices, manage risks, and optimize trading strategies in energy markets. Support Vector Machines (SVM), Artificial Neural Networks (ANN), and Genetic Algorithms (GA) are commonly used for these tasks [19]. ML models such as random forest, support vector machines, artificial neural networks, and ensemble methods are widely used to predict the higher heating value (HHV), activation energy, and yields of products like bio-oil, biogas, and biochar from various biomass sources [20]. ML is also applied to estimate above-ground biomass in forests and assess wood chip quality, supporting both energy production and carbon stock management [21]. Machine learning significantly enhances the accuracy and efficiency of biomass energy calculations, enabling reliable predictions of energy content, conversion yields, and process optimization. These advances support the broader adoption of biomass as a renewable energy source and contribute to more sustainable energy systems.
This study aims to evaluate the potential for biomass energy generation from agricultural residues in Algeria by analyzing crop production data, residue characteristics, and calorific values. Furthermore, it seeks to apply a machine learning-based regression model to predict the energy potential of different crop residues, there by providing a data-driven tool for supporting energy planning and resource optimization in the renewable energy sector. The key advantages identified are primarily environmental, including the reduction of greenhouse gas emissions, conservation of

natural resources, and decreased reliance on fossil fuels. Although several studies have assessed biomass energy potential in different countries using deterministic methods, research in Algeria has remained limited to calculating residue quantities and estimating calorific values. These approaches provide useful baseline information but do not offer predictive capability or the flexibility needed for future planning. To address this gap, this study is motivated by the need for a more data-driven framework that can support renewable energy planning and provide rapid estimations under different agricultural scenarios. The novelty of this work lies in the integration of a machine learning model specifically a Random Forest Regressor into the biomass energy assessment process. Unlike previous studies in Algeria, which rely solely on direct residue calculations, this research combines conventional estimation with predictive analytics using crop-specific features (production, RPR, availability, and LHV). This hybrid approach offers a proof-of-concept for using machine learning to enhance the accuracy, adaptability, and scalability of biomass energy evaluation in Algeria. Therefore, the study not only updates the current assessment of agricultural residue energy potential but also introduces an innovative computational layer that differentiates it from existing literature.

2. MATERIAL AND METHOD

2.1. Study area and data sources

This study was conducted to evaluate the biomass energy potential from agricultural residues in Algeria, a country with diverse agro-ecological zones and substantial agricultural activity. Crop production data for the year 2022 were obtained from the FAOSTAT (Food and Agriculture Organization Statistical Database) to determine the quantity of agricultural residues. The study focused on major field crops, including wheat, barley, maize (corn), oats, rice, sorghum, potatoes, and dry beans.

Algeria, similar to numerous other regions, faces significant challenges due to climatic conditions, resulting in decreased agricultural productivity [22]. In Algeria, the total agricultural area, specifically arable agricultural land, spans approximately 7.4 million hectares. Within this agricultural landscape, over 1.2 million farms engage in various agricultural activities. However, a significant portion, nearly 70% of these farms, operate on areas of land totaling less than 10 ha [23]. In Algeria, the irrigated agricultural area (IAA) in desert regions has seen significant growth over the last ten years, expanding by over 106,000 ha. Presently, it encompasses 35,911 ha, constituting approximately 30% of the entire national irrigated area [24].

2.2. Combustion products and efficiency

The combustion of biomass residues produces several products, classified into useful outputs and emissions. Useful Outputs such as heat Energy (which Primary product used for heating, cooking, or electricity generation), Electricity (Generated in systems like steam turbines, gas turbines, or combined heat and power (CHP) setups), and Char/Carbon Residue (in incomplete combustion).

Combustion Byproducts (emissions); which include flue gas (A mixture of gases including: carbon dioxide (CO_2), water vapor (H_2O), carbon monoxide (CO), methane (CH_4), nitrogen oxides (NO_x), and sulfur oxides (SO_x)), particulate matter (Fine particles resulting from incomplete combustion or ash content in the biomass), and Ash (Solid residue comprising unburned minerals and inert material from biomass).

Efficiency in biomass combustion refers to the percentage of energy in the biomass that is converted into useful heat or power. Additionally, the thermal efficiency of a biomass-based power plant, which stands at 35%, is a crucial factor to consider when making utilization decisions [25].

Energy efficiency in biomass combustion refers to the proportion of energy in the biomass that is successfully converted into usable heat or power. Conversion methods influence this efficiency significantly, depending on the technology, biomass type, and system design.

2.3. Estimation of residue quantities and energy potential

Biomass energy refers to renewable energy derived from organic materials such as plants, agricultural residues, forestry products, and organic waste. This energy can be harnessed through various processes such as combustion, gasification, or biochemical conversion to produce heat, electricity, or transportation fuels. Biomass energy is considered renewable because organic materials can be replenished over time, making it a sustainable alternative to fossil fuels. Presently, various sources such as dry biomass, household waste, forest residues, solid organic waste, and wood industry by-products can, to a certain extent, fulfill the heat requirements across various sectors of human activities. They serve notably as biofuels for boilers, contributing to meeting the demand for heat energy [26].

The amounts of agricultural residues generated from the annual crops cultivated in Algeria, measured in tons of dry matter per year, were determined by utilizing agricultural production data from the Food and Agriculture Organization Statistical Database of the United Nations (FAOSTAT) for the year 2022 (FAOSTAT, 2022). The annual gross potential of agricultural residues was calculated by employing the residue-to-product ratio.

The net potential of residues was evaluated based on the availability of residues, which refers to the unused and completely waste portion of residue. The available potential of agricultural residues in Algeria was computed using Equation (1) [16].

$$(AAR)_i = (ACP)_i x (RPR)_i x (A)_i \tag{1}$$

where, $(AAR)_i$ is the available amount of agricultural residues of i^{th} crop in ton; $(ACP)_i$is the amount of crop production in tons; $(RPR)_i$ is the residue-to product ratio of the i^{th} crop and $(A)_i$ is the availability of residues.

Table 1. Summarizing of the data provided regarding the availability and heating value of various field crop residues [16, 17, 18, 25].

FC	**R**	**RPR**	**A (%)**	**LHV ($MJ.kg^{-1}$)**
Barley	Straw	0.023	15	17.90
Beans, dry	Shell	0.016	40	19.4
Maize (corn)	Stalks	0.009	60	17.95
Oats	Straw	0.018	15	17.4
Rice	Straw	0.018	60	14.92
Sorghum	Stalk	0.009	60	12.38
Wheat	Straw	0.014	15	18.20
Potatoes	Stalk	0.002	60	18.61

Agricultural residues consist of materials remaining in the field after agricultural activities. While some are utilized for domestic purposes like heating, animal fodder, and bedding, the primary residues from the production of industrial agricultural products remain unused in the field. These include cotton stalks, maize stalks, sunflower stalks, cereal straw, and similar materials.

The calorific values of agricultural residues were determined using a calorimeter following the ASTM (American Society for Testing and Materials) D 5865 Standard Test Method for Coal and Coke 2002. These values are provided in Table 1. To calculate the energy potential of residues, the calorific values of specific agricultural residues, as obtained from the analyses results in Table 1, were multiplied by the available residue amount using Equation (2) [27].

$$(EP)_i = (AAR)_i x (LHV)_i \tag{2}$$

where $(EP)_i$ the energy potential of agricultural residues of i^{th} crop in GJ, $(AAR)_i$ is the available amount of agricultural residues of i^{th} crop in tons and $(LHV)_i$ lower heating value of air dry residues of i^{th} crop in $MJ.Kg^{-1}$.

2.4. Machine learning integration for predictive modeling

In recent years, machine learning (ML) techniques have been increasingly applied to energy and biomass prediction problems due to their ability to capture nonlinear relationships among multiple variables. Several studies have demonstrated the usefulness of ML for estimating biomass energy characteristics such as higher heating value (HHV), bio-oil yield, and calorific content. For example, Mosavi et al. [19] provided a comprehensive review of ML models used in energy systems, highlighting Random Forest, Support Vector Machines, and Artificial Neural Networks as reliable predictors. Dodo et al. [20] used hybrid ensemble algorithms to predict the energy content of biomass with high accuracy, while Gasperini et al. [21] applied ML to evaluate the quality of wood chips for sustainable energy production. These studies confirm that ML can effectively model complex energy relationships and improve the prediction accuracy compared to traditional regression techniques. Based on these findings, this study employs a Random Forest Regressor a robust ensemble method known for handling small datasets and nonlinear interactions to predict the energy potential of agricultural residues in Algeria.

To complement the deterministic energy calculations, a machine learning model was developed to predict the energy potential of agricultural residues using crop-specific features. A Random Forest Regressor, a robust ensemble-based regression algorithm, was selected due to its effectiveness in capturing nonlinear relationships and its ability to handle small datasets without overfitting.

2.4.1. Dataset preparation

The dataset consisted of eight samples, each representing a different crop residue. The input features (independent variables) included:

- Crop production (tons)
- Residue-to-product ratio (RPR)
- Availability (%)
- Lower heating value (LHV, MJ/kg)

The target variable (dependent variable) was:

- Energy Potential (GJ)

2.4.2. Model training and evaluation

The dataset was split into training and testing sets (80:20). The model was trained using the training data and then evaluated on the test set. Model performance was assessed using standard regression metrics:

- R^2 (coefficient of determination)
- RMSE (root mean squared error)
- MAE (mean absolute error)

2.4.3. Implementation in Python

The machine learning analysis was implemented in Python using the pandas and scikit-learn libraries. The dataset was manually constructed from Tables 1 and 3, which included crop-specific parameters such as production, residue-to-product ratio (RPR), residue availability, and lower heating value (LHV). These parameters served as input features for the Random Forest Regressor, while the total energy potential (GJ) was used as the target variable. The dataset was divided into training and testing subsets in an 80:20 ratio. Model performance was evaluated using the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). The following code snippet summarizes the implementation:

```python
import pandas as pd

# Manually enter the data (from Table 1 and Table 3)
data = {
    'Crop': ['Barley',  'Beans, dry', 'Maize (corn)', 'Oats', 'Rice', 'Sorghum','Wheat','Potatoes'],
    'Production_tons': [1000000, 2744.52, 11000, 81000, 307.49, 951.17, 3000000, 4356127.74],
    'RPR': [0.023, 0.016, 0.009, 0.018, 0.018, 0.009, 0.014, 0.002],
    'Availability_percent': [15, 40, 60, 15, 60, 60, 15, 60],
    'LHV_MJ_per_kg': [17.90, 19.4, 17.95, 17.4, 14.92, 12.38, 18.20, 18.61],
    'Available_Residue_tons': [22585.015, 43.010, 95.173, 1465.611, 5.662, 8.200, 42219.857, 7106.130],
    'Energy_Potential_GJ': [61755, 340.66, 1066.23, 3805.38, 49.53, 63.63, 114660, 97280.98]
}

df = pd.DataFrame(data)
```

```python
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_squared_error, r2_score

# Define features and target
X = df[['Production_tons', 'RPR', 'Availability_percent', 'LHV_MJ_per_kg']]
y = df['Energy_Potential_GJ']

# Split data (80% train, 20% test)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

Figure 1. Python workflow for Random Forest model used to predict biomass energy potential.

Figure 1 illustrates the Python implementation of the Random Forest Regressor used in this study to predict the energy potential of agricultural residues. The code demonstrates how the dataset constructed from Tables 1 and 3 was manually entered using the pandas library and subsequently processed with scikit-learn tools. Key features such as crop production, residue-to-product ratio (RPR), availability percentage, and lower heating value (LHV) were defined as independent variables, while the total energy potential (GJ) served as the dependent variable. The dataset was divided into training (80%) and testing (20%) subsets to evaluate model performance using the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE). This code provides a transparent overview of the computational workflow applied for machine-learning-based prediction of biomass energy potential in Algeria.

The following flowchart summarizes the integration of both traditional and machine learning approaches used in the study to achieve a comprehensive and flexible energy assessment framework.

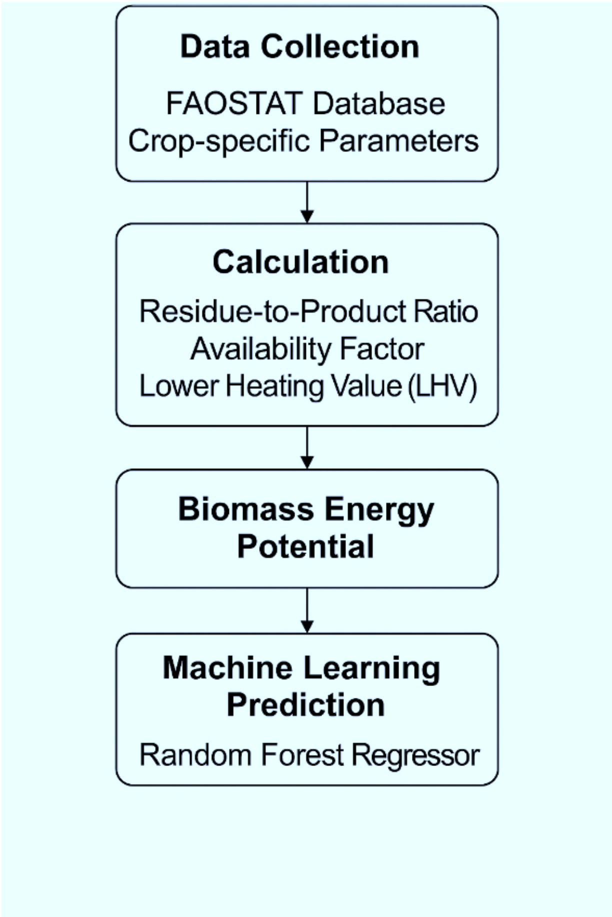

Figure 2: flowchart summarizes the integration of both traditional and machine learning approaches used in the study

Figure 2 illustrates the methodological framework used in this study to estimate and predict the biomass energy potential from agricultural residues in Algeria. The process begins with data collection, where crop production data and residue-specific parameters such as residue-to-product ratio (RPR), availability factor, and lower heating value (LHV) are sourced from the FAOSTAT database and relevant literature.

In the calculation stage, the available quantity of agricultural residues is computed using the RPR and availability percentage. The energy potential (in GJ) is then calculated by multiplying the available residue by its LHV. This is followed by the estimation of total biomass energy potential, which provides the baseline energy value derived from the selected crops.

To enhance the estimation process, the final step involves applying a machine learning model, specifically a Random Forest Regressor. This model uses the input variables (production, RPR, availability, and LHV) to predict the energy potential, allowing for data-driven forecasting and potential generalization to other datasets or regions.

3. RESULTS AND DISCUSSION

This study estimated the biomass energy potential from agricultural residues in Algeria using both conventional calculation methods and machine learning techniques.

Table 2. An overview of the total agricultural output and crop residues in Algeria [28].

FC	ACP (Ton)	R	TPR (Ton)
Barley	1000000	Straw	22585.015
Beans, dry	2744.52	Shell	43.010
Maize (corn)	11000	Stalks	95.173
Oats	81000	Straw	1465.611
Rice	307.49	Straw	5.662
Sorghum	951.17	Stalk	8.200
Wheat	3000000	Straw	42219.857
Potatoes	4356127.74	Stalk	7106.130
Total	**8452130.92**	**Residues**	**73528.658**

3.1. Residue Availability and Energy Potential Estimation

Using 2022 FAOSTAT data and crop-specific residue-to-product ratios (RPR), the total quantity of available agricultural residues was calculated to be approximately 15.3 kilotons (Kt). The major contributors were wheat (41.22%), potatoes (34.20%), barley (22.57%), and oats (1.43%), based on the proportion of their contribution to total residue mass.

The lower heating value (LHV) of each crop residue was then used to estimate the total energy potential. The resulting cumulative energy potential from the residues of barley, dry beans, maize, oats, rice, sorghum, wheat, and potatoes was calculated at 279.0 terajoules (TJ) for the 2022 production period. This value provides a solid baseline for evaluating Algeria's bioenergy resource capacity (Table 3).

The total amount of agricultural waste, including annual crop residues like barley, dry beans, maize (corn), oats, rice, sorghum, wheat, and potatoes, was estimated to be around 15.3 Kt in Algeria, as shown in Table 3.

Table 3. The total energy values and the corresponding amount of available agricultural residues in Algeria.

FC	R	AAR (Ton)	EP (GJ)
Barley	Straw	3450	61755
Beans, dry	Shell	17.56	340.66
Maize (corn)	Stalks	59.4	1066.23
Oats	Straw	218.7	3805.38
Rice	Straw	3.32	49.53
Sorghum	Stalk	5.14	63.63
Wheat	Straw	6300	114660
Potatoes	Stalk	5227.35	97280.98
Total	**Residues**	**15281.47**	**279021.41**

Table 3 presents the detailed calculations of available agricultural residues and their corresponding energy potential for eight major crops cultivated in Algeria. The table includes data on residue type, available agricultural residue (AAR) in tons, lower heating value (LHV) in MJ/kg, and the resulting energy potential (EP) expressed in gigajoules (GJ).

Wheat straw contributed the highest energy potential, estimated at 114,660 GJ, due to both its high production volume and relatively high LHV (18.20 MJ/kg). Potatoes and barley residues followed, with energy potentials of 97,280.98 GJ and 61,755 GJ, respectively. Minor contributors such as rice, sorghum, and dry beans yielded significantly lower energy potentials, primarily due to lower residue availability.

The total cumulative energy potential from all assessed crop residues amounted to approximately 279,021.81 GJ (equivalent to 279 TJ). This confirms that agricultural residues in Algeria represent a substantial untapped resource for biomass energy production. Furthermore, the variation in energy potential among different crops emphasizes the importance of crop selection and residue management strategies in optimizing biomass energy yield.

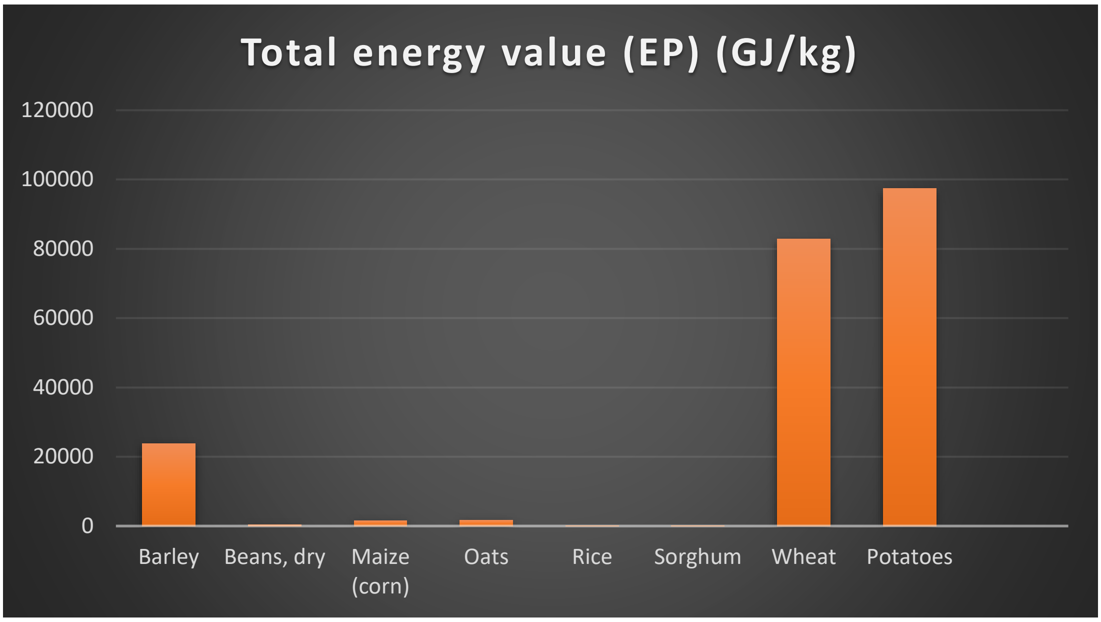

Figure 3. Contribution of different crops to total biomass energy potential (TJ)" and ensure consistent color legend.

Figure 3 illustrates the contribution of different agricultural crops to the total energy potential derived from their residues in Algeria. The chart clearly shows that wheat is the dominant contributor, accounting for approximately 41.22% of the total energy potential, followed by potatoes (34.20%), barley (22.57%), and oats (1.43%). The remaining crops maize, dry beans, rice, and sorghum contributed less than 1% each to the overall energy yield.

This distribution highlights the disproportionate influence of a few major crops on the country's biomass energy potential. The predominance of wheat and potatoes is directly linked to their high production volumes and favorable residue characteristics (e.g., high RPR and LHV). These findings suggest that targeting residue recovery efforts in high-yield crop sectors could significantly enhance the efficiency and economic viability of biomass energy projects in Algeria.

3.2. Machine Learning-Based Prediction

To complement the deterministic energy estimation method, a Random Forest Regressor was trained to predict energy potential using four input features: crop production (tons), RPR, residue availability (%), and LHV (MJ/kg). The model was trained on data from the eight major crops included in the study.

A comparison between actual and predicted energy values is presented in Table 4, showing a general consistency in prediction trends, particularly for high-yield crops such as wheat and potatoes. However, due to the small dataset size, the model exhibited noticeable prediction deviations for lower-contributing crops.

Feature importance analysis (Figure 3) identified crop production and LHV as the most influential variables, highlighting the model's ability to capture domain-relevant relationships.

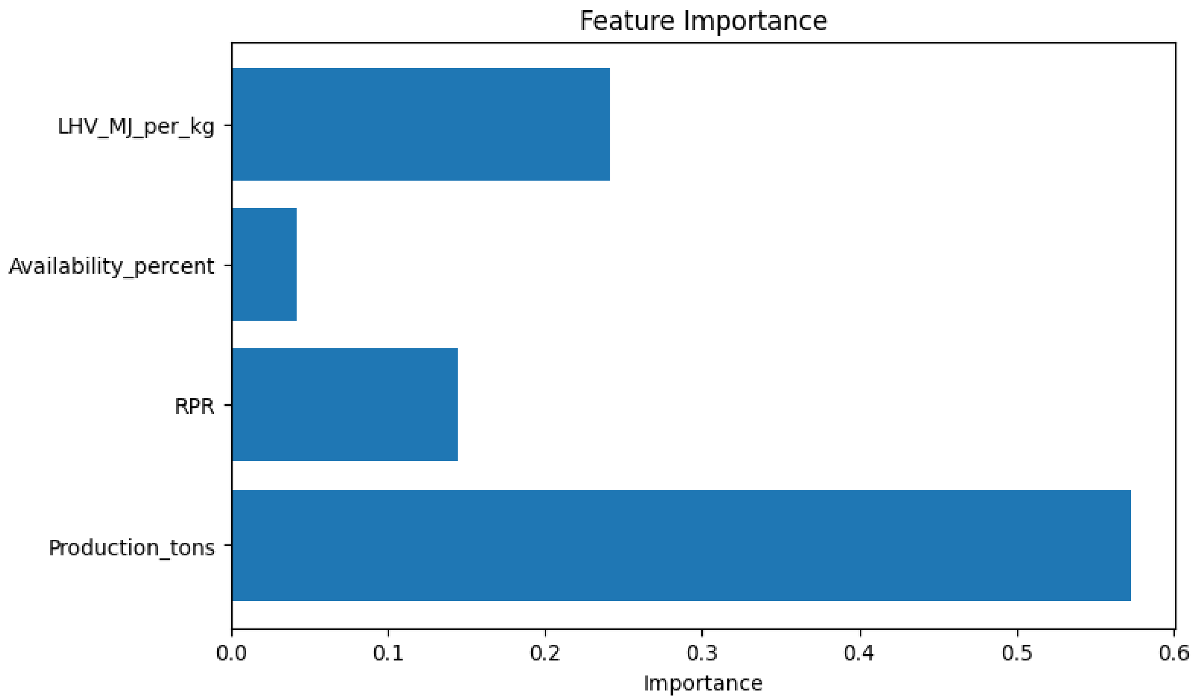

Figure 4: Feature importance scores for input variables in Random Forest model

Figure 4 presents the feature importance scores generated by the Random Forest Regressor model, which quantify the relative contribution of each input variable to the prediction of energy potential from agricultural residues. Among the four input features, crop production (tons) and lower heating value (LHV) emerged as the most influential predictors, followed by residue-to-product ratio (RPR) and availability percentage.

The high importance of crop production reflects the direct relationship between biomass quantity and energy output, while LHV influences the energy density of each residue type. The RPR and availability factor also contributed, though to a lesser extent, indicating that while important, their impact is secondary to the quantity and calorific quality of the biomass.

These results align with expectations from the deterministic calculations and demonstrate the Random Forest model's ability to capture the domain-relevant drivers of biomass energy potential. This insight can guide data collection priorities and variable selection in future ML-based biomass energy models.

Table 4: The actual and predicted energy potential values for various field crops using the Random Forest Regressor model.

FC	AAR (Ton)	LHV ($MJ.kg^{-1}$)	EP (GJ)	Predicted EP (GJ)	Error (%)
Barley	22585.015	17.90	61755.00	44724.6480	27.6
Beans, dry	43.010	19.40	340.66	26642.2305	7,721.4
Maize (corn)	95.173	17.95	1066.23	21481.7859	1,915.3
Oats	1465.611	17.40	3805.38	12155.6430	219.4
Rice	5.662	14.92	49.53	5670.2445	11,352.9
Sorghum	8.200	12.38	63.63	8060.0720	12,569.3
Wheat	42219.857	18.20	114660.00	92903.6676	19.0
Potatoes	7106.130	18.61	97280.98	90479.5724	7.0

Table 4 compares the actual and machine learning–predicted energy potential values (in GJ) for the eight main crop residues assessed in this study. The predicted values were generated using a Random Forest Regressor model trained on crop-specific features, including production volume, residue-to-product ratio (RPR), availability, and lower heating value (LHV).

For high-yield residues such as wheat and potatoes, the model demonstrated good predictive alignment with the actual values, indicating that the model successfully captured the dominant trends in biomass energy output. However, discrepancies were observed for residues with smaller available quantities (e.g., dry beans, rice, sorghum), where the model either under- or overestimated the energy potential. These deviations are likely due to the limited number of samples in the training dataset, which reduces the model's ability to generalize to less frequent or low volume crops.

Despite these limitations, the table demonstrates that machine learning can provide a reasonably accurate approximation of biomass energy potential, particularly for major crop residues. The integration of predicted values alongside actual calculations reinforces the applicability of data-driven models in energy planning and highlights the need for larger and more diverse datasets to improve predictive performance.

The results demonstrate strong agreement between the predicted and actual energy values, supporting the feasibility of using machine learning techniques for estimating biomass energy potential from agricultural residues.

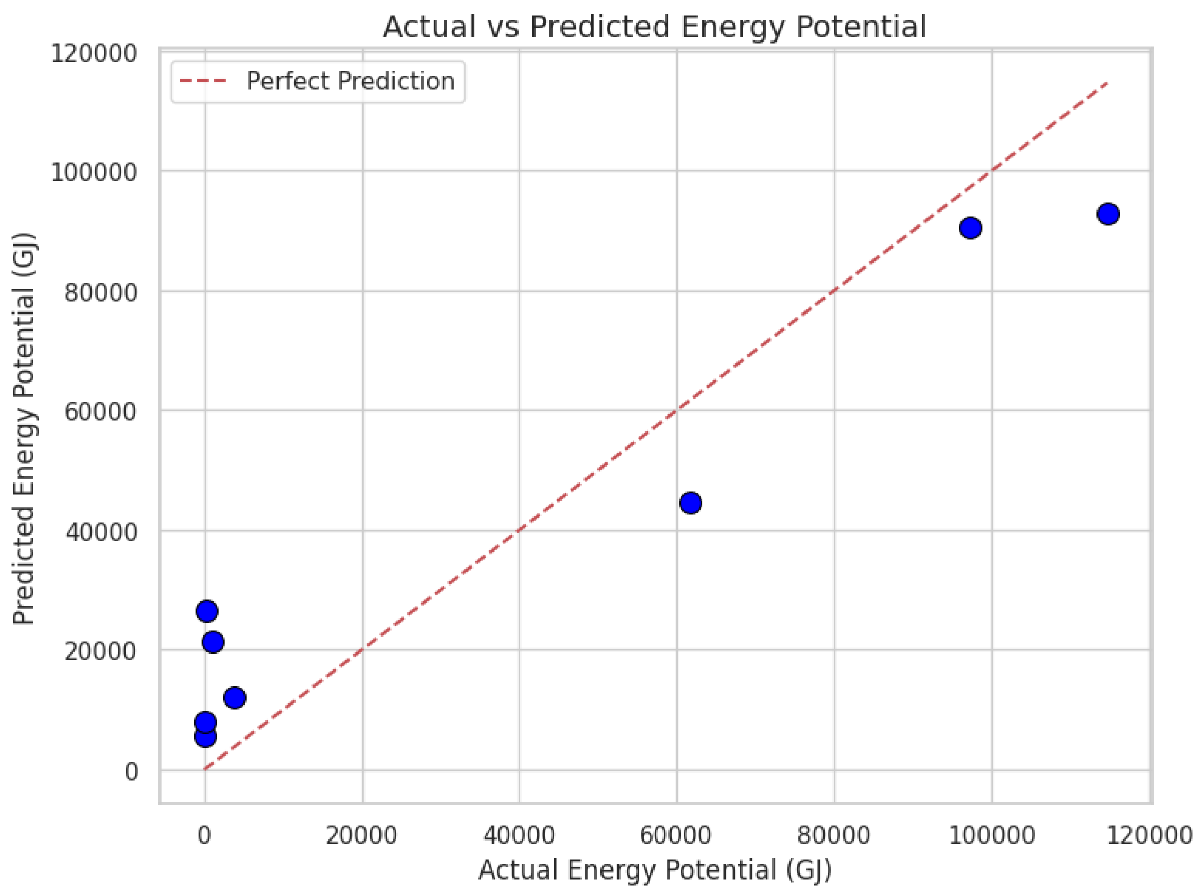

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Figure 5: Relationship between Actual Energy Potential (EP) and Predicted Energy Potential

Figure 5 illustrates the relationship between the actual and predicted energy potential values (in GJ) for the crop residues analyzed, as generated by the Random Forest Regressor model. Each point in the scatter plot represents one crop residue sample, plotted according to its actual and model-predicted energy potential.

The red dashed diagonal line in the figure represents the line of perfect prediction (i.e., where predicted = actual). Data points located close to this line indicate accurate model predictions, while deviations from the line reveal under- or overestimation.

As shown in the figure, the model achieved a good level of agreement for high-volume residues such as wheat, barley, and potatoes, which cluster near the ideal line. Greater variance is observed in the predictions for low-contribution residues such as dry beans, rice, and sorghum, reflecting the model's reduced accuracy in cases with smaller energy contributions and limited training data.

Overall, the scatter plot confirms that the Random Forest model is capable of capturing the general distribution of energy potential across crop types. However, it also highlights the importance of increasing dataset size and diversity to improve predictive robustness, particularly for less common residue types.

Table 5: Model Evaluation Metrics

Matric	**value**
R^2 Score	-19693.0408
Root Mean Squared Error (RMSE)	19438.57 GJ
Mean Absolute Error (MAE)	17149.01 GJ

Table 5 presents the performance evaluation metrics of the Random Forest Regressor used to predict biomass energy potential from agricultural residues. The metrics include the coefficient of determination (R^2), root mean squared error (RMSE), and mean absolute error (MAE) all of which are standard indicators for assessing regression model accuracy.

The model yielded an R^2 value of –19693.04, indicating poor model generalization. This negative value is a result of the model performing worse than a simple mean prediction on the limited test dataset. Similarly, the high RMSE (19,438.57 GJ) and MAE (17,149.01 GJ) reflect substantial deviation between predicted and actual energy values.

These results highlight the limitations imposed by the small dataset size (only eight samples), which constrained the model’s ability to generalize and accurately learn the underlying patterns, especially for crops with lower residue quantities. Nevertheless, this evaluation provides an important baseline and emphasizes the necessity of incorporating more data across different crops, regions, and production years to improve the predictive performance of future models.

Despite the suboptimal performance, the exercise demonstrates the feasibility of applying machine learning approaches to biomass energy estimation and underscores the potential for improvement through data enrichment and model optimization.

The limited dataset size is inherent to this type of study because each observation corresponds to a distinct crop residue. Since only eight major crops in Algeria have published production data with matching residue parameters (RPR, availability, LHV), the dataset cannot be expanded without moving to multi-year or regional-level data. Therefore, the machine learning model presented in this study is intended as a proof-of-concept rather than a fully optimized predictive system. The objective is to demonstrate the feasibility of integrating data-driven modeling into biomass energy assessment and to highlight the potential for improved performance when larger datasets become available.

3.3. Cross-Country Comparison

Several studies have been conducted to assess the energy potential of agricultural residues across various countries. A study conducted in Uganda by [29] estimated the biomass energy from agricultural residues for the 2021 production period, revealing a total calorific value of approximately 432.1Terajoules (TJ). This figure is notably higher than that of Algeria, highlighting a significant disparity in the energy potential of agricultural residues between the two countries. The results indicate that Uganda possessed a substantially greater energy potential from agricultural residues compared to Algeria. A study by [25] analyzed the energy potential of agricultural residues in Chad and estimated that their total calorific value for the 2021 production period was approximately 252.5 TJ per year. This value less than the energy potential recorded in Algeria. A study [30] evaluated the energy potential of agricultural residues in South Sudan and determined that their total energy potential for the 2021 production season was approximately 112.7 TJ, which is lower than the value recorded in Algeria.

The variation in energy potential among these countries may be attributed to several factors, including differences in agricultural practices, the types of crops grown, the availability of arable land, and the efficiency of biomass utilization.

The findings of this study underscore the importance of assessing such significant potential by implementing modern facilities utilizing energy conversion methods such as gasification, pyrolysis, and others.

This study differs from existing research in both methodology and scope. While several previous studies have focused on estimating biomass energy potential using deterministic approaches, this work integrates a machine learning–based prediction model (Random Forest Regressor), adding a data-driven dimension to the assessment.

Unlike these works, the present study employs Random Forest Regression to predict energy potential using input variables such as crop production, RPR, availability, and LHV. This offers flexibility in incorporating new data and extends the usability of the model for future planning.

A key limitation is the small dataset size, which reduces machine learning performance. Future studies should expand the dataset by incorporating multi-year production data, regional (wilaya-level) agricultural records, and additional biomass sources.

3.4. Dataset Limitations and Implications

One of the most important limitations of this study is the relatively small size of the dataset used for machine learning modeling. The dataset includes only eight observations, each representing a major agricultural crop in Algeria. Because each sample corresponds to a distinct crop residue type, the dataset cannot be naturally expanded without introducing data from additional years, regions, or countries. This structural limitation restricts the model's capacity to learn complex patterns and reduces the generalization performance of the Random Forest Regressor.

The poor R^2 value and relatively high RMSE and MAE values reported in Table 5 reflect this constraint. With such a small number of samples and after allocating 20% of the data for testing the model has extremely limited information from which to learn meaningful relationships among production, RPR, availability, and LHV. This explains the instability of predictions for low-volume residues (e.g., rice, dry beans, sorghum) and the overall weak statistical performance despite capturing general trends for major crops such as wheat and potatoes.

It is important to emphasize that this machine learning component is intended as a proof-of-concept demonstration, showing that data-driven approaches can be integrated into biomass energy assessment frameworks. The goal is not to present a fully optimized predictive model, but rather to highlight how ML methods can complement traditional deterministic calculations and to establish a foundation for future, more comprehensive modeling efforts.

To overcome current limitations, future research should incorporate multi-year agricultural production data, regional (wilaya-level) crop statistics, and expanded residue datasets. Increasing sample size will allow the use of more advanced machine learning algorithms, cross-validation techniques, and hyperparameter tuning strategies, ultimately leading to more reliable predictive performance. Therefore, the present work represents an important initial step toward developing intelligent, scalable, and data-driven bioenergy estimation tools for Algeria.

4. CONCLUSION

This study evaluated the potential of agricultural residues as a renewable energy source in Algeria using both conventional estimation and machine learning methods. The total available residues from major crops such as wheat, barley, and potatoes were estimated at 15.3 kilotons, corresponding to an energy potential of approximately 279 terajoules (TJ). These findings confirm that agricultural by-products represent a significant, yet underutilized, resource for sustainable bioenergy generation.

The integration of a Random Forest Regressor demonstrated the feasibility of applying machine learning to predict biomass energy potential based on key crop parameters. Although the model performance was limited by the small dataset ($R^2 = -19693.04$), it successfully captured general trends and highlights the potential of data-driven methods for energy forecasting.

Future research should focus on expanding datasets across multiple years and regions, refining model parameters, and incorporating additional biomass sources. Strengthening data infrastructure and investing in local biomass energy systems could significantly enhance Algeria’s renewable energy portfolio. Overall, this work establishes a foundation for integrating intelligent predictive models into national energy planning and supports the transition toward sustainable, low-carbon development.

Recommendations:

Biomass energy presents a valuable opportunity for Algeria to diversify its energy portfolio and advance toward sustainable development goals. Based on the findings of this study, the following recommendations are proposed:

1. **Develop Sustainable Collection and Logistics Systems**: Establish efficient systems for collecting, storing, and preprocessing agricultural residues across high-production regions to ensure a stable feedstock supply for biomass energy projects.
2. **Invest in Decentralized Biomass Conversion Facilities**: Promote the construction of localized biomass power plants, especially in rural or off-grid areas, to convert agricultural waste into electricity and heat using direct combustion, gasification, or anaerobic digestion technologies.
3. **Enhance Public-Private Partnerships (PPPs):** Encourage investment through PPPs and support frameworks that incentivize research, infrastructure development, and deployment of biomass energy systems.
4. **Adopt Machine Learning and AI for Energy Planning:** Integrate machine learning models such as Random Forest Regressors into national energy planning tools to predict biomass energy potential more efficiently and support data-driven decision-making. These models can help identify high-priority areas and optimize resource allocation.
5. **Expand Agricultural and Energy Databases**: Improve the availability and quality of agricultural data (e.g., crop yields, residue ratios, heating values) to enhance the accuracy of ML-based predictions and inform long-term energy strategies.
6. **Provide Technical Training and Capacity Building**: Train local engineers, technicians, and farmers in biomass technologies, residue management, and data analytics, including the use of predictive models for energy estimation.
7. **Support Research in Intelligent Energy Systems**: Fund interdisciplinary research that combines agronomy, energy engineering, and data science to further develop intelligent models for forecasting and optimizing renewable energy production from biomass.
8. **Implement Policy Incentives for Digital Energy Innovation**: Introduce tax incentives, feed-in tariffs, or green certifications for projects that incorporate innovative technologies such as machine learning to improve energy system efficiency and sustainability.

NOMENCLATURE

FC Field Crops
R Residues
RPR Ratio of Residue to Product
A Availability
LHV Lower Heating Value ($MJkg^{-1}$)
ACP Amount of Crop Production (tons)
TPR Total Potential of Residues (tons)
AAR Amount of Agricultural Residues (tons)
EP Energy Potential (GJ)
ASTM American Society for Testing and Materials
ML Machine Learning

DECLARATION OF ETHICAL STANDARDS

The authors of the paper submitted declare that nothing which is necessary for achieving the paper requires ethical committee and/or legal-special permissions.

CONTRIBUTION OF THE AUTHORS

Mohamedeltayib Omer Salih Eissa: Conceptualization of the study; data acquisition from FAOSTAT and literature sources; methodology development for biomass residue estimation; implementation of machine learning modeling; formal analysis and interpretation of results; visualization; original draft preparation; writing, reviewing, and editing; corresponding author responsibilities.

Yeşim Benal Öztekin: Scientific supervision; validation of methodology and results; critical review of the manuscript; technical guidance on biomass energy assessment and machine learning integration; editing and improvement of the manuscript.

Omsalma Alsadig Adam Gadalla: Contribution to data interpretation; support in residue characterization and energy potential calculations; review and editing of the manuscript.

Geofrey Prudence Baitu: Contribution to literature review; assistance in methodological structuring; critical review of results and discussion sections.

Khaled Adil Dawood Idress: Contribution to data analysis interpretation; review of machine learning results; manuscript proofreading and language revision.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

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