ASSESSING THE PROPERTIES OF *MISCANTHUS X GIGANTEUS* UNDER VARYING LEVELS OF ASH FERTILIZATION TREATMENT AND REGRESSION NEURAL NETWORK INSIGHT INTO CALORIFIC VALUE

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The aim of the study was to investigate the changes in ultimate, proximate analysis and calorific properties of Miscanthus x Giganteus with three types of planting materials (two rhizomes - R1 and R2 - and one seedling – S) and three ash fertiliser treatments (P_0, P_2, and P_5) were included in the study. The research further examined their effects on crop yield, stem height and various chemical properties. The results showed that the maximum yield was obtained with the R1 x P_2 plant type, while the minimum yield was recorded with the R2 x P_2 plant type. In addition, the greatest average stem height (3.34 m) was recorded for the R2 x P_5 plant type. Significant differences were also found in the chemical components between the plant types and treatments. For example, the highest ash content of 2.25% was found in plant type 'S' x P_5, while the highest coke content of 14.48 % was found in plant type R1 x P_5. The statistical analysis confirmed that planting material and ash fertilisation had significant influence on the physicochemical properties of Miscanthus x Giganteus. This consequently affects the calorific value, with the average higher and lower heating value being 18.32 and 17.04 MJ/kg, respectively. The neural regression network models showed robust predictive performance for the higher (HHV) and lower heating value LHV, with low chi-square values (X^2) and high coefficients of determination (R^2).

Key words*: Miscanthus x Giganteus, fertilisation, energy properties, artificial neural network, modelling.*

1. Introduction

Energy derived from biomass plays a crucial role in achieving the European Union's renewable energy targets for 2030 and beyond. However, this promising sector must manage the complexity of producing, processing and using biomass in a way that is both sustainable and efficient. Key to this strategy is achieving a balance that optimises greenhouse gas mitigation and preserves ecosystem services [1-3]. Compared to seed propagation, vegetative propagation of triploid *Miscanthus x Giganteus* is cost-intensive, making rhizomes the preferred choice for planting material due to their integral role in vegetative propagation [4]. This biomass source not only has the potential to reduce greenhouse gas and pollutant emissions generally associated with increased fossil fuel use [5], but also offers exceptional opportunities for energy production due to its dense growth [6]. However, to realise the full potential of *Miscanthus x Giganteus* as a bioenergy feedstock, effective nitrogen and harvest management strategies are required [7], highlighting the need for targeted cultivation practises. Importantly, *Miscanthus x Giganteus* also has the added benefit of sequestering carbon in the soil, further contributing to climate change mitigation [8]. Morozova et al., (2020) [9] in research reports the average values of *Miscanthus x Giganteus* in the range of 20.5 – 30.4 t DM/ha in relation to different harvest periods. The increase in the global use of biomass for energy generation has implications for waste management, particularly in terms of the escalating volumes of biomass ash produced. Conventional landfill disposal methods are not only costly, but also result in potentially valuable resources being thrown away [10]. As an alternative, use biomass ash can as a fertiliser [11], which enriches agricultural soils with valuable nutrients, especially if mineral fertilisers are not used. This approach is not only resource-efficient, but also environmentally conscious and carries minimal risk of harmful environmental impacts [12]. Application of fly ash not exceeding 25% of soil weight can strengthen plant biomass while maintaining lower metal(loid) concentrations, potentially improving agricultural yields [13]. As a fertiliser, wood ash provides readily available nutrients such as phosphorus, calcium, magnesium, potassium and boron. It can increase soil pH and concentrations of the main nutrients while reducing the availability of aluminium and less important elements. It also reduces manganese toxicity, which could improve crop yields [14]. Ash in composting improves humification of organic matter and nutrient content, improving compost quality and plant health. It also helps to reduce volatile solids and improve the stability of the compost, increasing its marketability [15]. Ma et al., (2021) [16] notes that *Miscanthus × giganteus* shows inconsistent responses to nitrogen fertiliser, possibly influenced by environmental factors, soil types, nitrogen sources, plant age and timing of fertilisation. Fertilisation may possibly affect the associated microbial community in the soil, but the exact mechanisms remain unknown. Smith & Slater, (2010) [17] conducted a study on the effects of organic (cattle and pig manure, chicken litter and unlimed and limed sewage) and inorganic fertiliser (NPK) application on energy crops in Wales, including *Miscanthus x Giganteus*, *Arundo donax* and *Phalaris arundinacea*. The study found that *Miscanthus x Giganteus* responded with increased growth in the second year to all fertilisers applied, with inorganic nitrogen applications being more effective than organic fertilisers. Adjuik et al., (2020) [18] investigated the effects of different fertiliser treatments on biomass yield and greenhouse gas emissions of *Miscanthus x Giganteus* grown on set-aside agricultural land. No significant differences were found between the treatments, which included digestate from the biogas plant, synthetic fertiliser (urea), hydrochar and a control. Due to its robust combustion properties, *Miscanthus x Giganteus* can be used as a biofuel, especially in the form of pellets or briquettes [19]. In recent years, machine learning techniques have gained prominence in the renewable energy production sector, particularly in the area of modelling and prediction [20]. These computational strategies, such as artificial neural networks have been used to improve the prediction of biomass gasification process outcomes [21]

In view of the evidence presented in the above findings, it is intended to further investigate the effects of different planting patterns and different ash treatments on the physicochemical composition and energy potential of *Miscanthus x Giganteus* biomass. The feasibility of implementing artificial neural network regression models to estimate calorific value will also be evaluated.

2. Materials and methods

2.1. Establishment of the crop and application of ash fertiliser measures

At the University of Zagreb experimental site (Zagreb, Croatia), an experimental field was established to investigate the impact of ash fertilization on the growth dynamics of *Miscanthus x Giganteus*. Three types of plant material were used for the experiment: rhizomes of the Croatian genotype (R1), rhizomes of the English origin (genotype R2) and seedlings of the Polish genotype (S). The rhizomes and seedlings are planted in plots of 4 m x 10 m (40 m^2), while the seedlings are planted in plots of 2.4 m x 10 m (24 m^2). A distance of 3 m is maintained both between plots and between replicates. The experimental design followed a split-split plot scheme with three repetitions, resulting in a total of 27 primary plots. The main factor in the experiment is the type of planting material (R1, R2, S), the sub-factor is the ash fertilisation (P_0, P_2, P_5).

2.2. Physicochemical and calorimetric analysis

From the experimental point of view, the analysis of *Miscanthus x Giganteus* biomass was performed in the laboratory of the University of Zagreb, Faculty of Agriculture, according to standard testing methods. Within the scope of the study, several analyses were performed on the sample. Dry matter analysis (DM) was performed using a Memmert laboratory dryer [22] according to the procedure specified in CEN /TS 14774-2:2009 [23]. Proximate Analysis, which included the evaluation of ash, coke, volatile matter (VM), and Fixed Carbon (FC) concentration, was performed using the method of burning the oven-dry sample in a crucible in a muffle furnace [24] according to EN ISO 18122:2015 [25] and CEN /TS 15148:2009 [26]. Ultimate Analysis encompassed the measurement of carbon (C), hydrogen (H), nitrogen (N), oxygen (O) and sulphur (S) using a Vario Macro CHNS analyzer [27] as described in the standards EN 15104:2011 [28] and EN 15289:2011 [29]. The heating value, in particular the HHV, was determined using an adiabatic bomb calorimeter [30] according to the method CEN /TS 14918:2005 [31].

2.3. Data processing

After the laboratory analyses, the data obtained were analysed using TIBCO Statistica 13.3.0 software (Palo Alto, CA, USA; 2017) [32]. In addition to basic statistical methods, principal component analysis (PCA) was also performed to reduce the dimensionality of the data and identify the most significant variability within the dataset, allowing for a better understanding of hidden structural patterns [33]. In parallel with the previously described methods, a univariate analysis was carried out to determine the influence of parameters such as the type of planting material, ash treatment and their interactive effects on the changes in biomass properties of *Miscanthus x Giganteus*.

2.4. Regression neural network modelling of calorific value

The last part of the research involved building a regression model in the form of an artificial neural network to estimate the energy values (HHV and LHV) of *Miscanthus x Giganteus* biomass based on the input parameters of the ultimate analysis. The first step was to split the data into 70% for learning and 30% for testing the model, which is considered a standard data split [34]. After data preparation, the regression models were built according to the following equation (1) [35]:

$$Y = f_1(W_2 \cdot f_2(W_1 \cdot X + B_1) + B_2) \tag{1}$$

Where Y is the output value; f_1, f_2 - transfer functions of the hidden and output layers; $W_{1,2}$ - weight coefficients of the hidden and output layers; $B_{1,2}$ - hidden and output layer biases.

After calculating the output values, statistical error tests and residual analyses were performed, including Chi-square test (X^2) (2), Root Mean Square Error (RMSE) (3), Mean Bias Error (MBE) (4), Mean Percentage Error (MPE) (5), Sum Squared Error (SSE) (6), Average Absolute Relative Error (AARD) (7) and Coefficient of Determination (R^2) (8) [36,37]:

$$x^2 = \frac{\sum_{i=1}^{N}(x_{p,i} - x_{e,i})^2}{N - n} \tag{2}$$

$$RMSE = \left[\frac{1}{N} \cdot \sum_{i=1}^{N}(x_{p,i} - x_{e,i})^2\right]^{1/2} \tag{3}$$

$$MBE = \frac{1}{N} \cdot \sum_{i=1}^{N}(x_{p,i} - x_{e,i}) \tag{4}$$

$$MPE = \frac{100}{N} \cdot \sum_{i=1}^{N}\left(\frac{\left|x_{p,i} - x_{e,i}\right|}{x_{e,i}}\right) \tag{5}$$

$$SSE = \sum_{i=1}^{N}(x_{p,i} - x_{e,i})^2 \tag{6}$$

$$AARD = \frac{1}{N} \cdot \sum_{i=1}^{N}\left|\frac{x_{e,i} - x_{p,i}}{x_{e,i}}\right| \tag{7}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left[x_i^p - x_i^e\right]^2}{\sum_{i=1}^{n}\left[x_i^p - x^m\right]^2}, \quad x_m = \frac{\sum_{i=1}^{n} x_i^e}{n} \tag{8}$$

Where p in the index and exponent stands for predicted values; e in the index and exponent for experimentally determined values.

The last part of optimizing neural network regression models involved the method of global sensitivity based on the data obtained by artificial neural networks to find the optimal pattern. The Yoon's global sensitivity method was used according to the following formula (9) [38]:

$$RI_{ij}(\%) = \frac{\sum_{k=0}^{n}(w_{ik} \cdot w_{kj})}{\sum_{i=0}^{m}\left|\sum_{k=0}^{n}(w_{ik} \cdot w_{kj})\right|} \cdot 100\% \tag{9}$$

3. Results

3.1. Yield

Figure 1 shows a graphical representation of the yield and average plant height of *Miscanthus x Giganteus* in the study conducted.

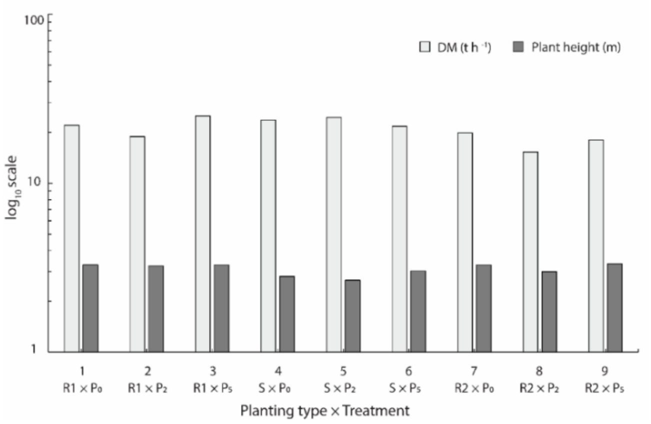

Figure 1. *Miscanthus x Giganteus* yield and plant height regarding planting type and ash treatment

To facilitate plotting yield and plant height variables on the y-axis, a logarithmic scale was used as a method to adjust the resolution of the data in the plot [39].

3.2. Ultimate analysis

The table 1 presents the results of a study examining the impact of different treatments (P_0, P_2, P_5) on three different planting types (R1, S, R2), assessing ultimate analysis.

Table 1. Ultimate analysis of studied biomass of different *Miscanthus x Giganteus* in relation to different planting material and ash treatment

No.	Planting type	Treatment	N (%)	C (%)	S (%)	H (%)	O (%)
1		P_0	$0.57{\pm}0.17^{a}$	$50.8{\pm}0.55^{a}$	$0.05{\pm}0.02^{a}$	$5.77{\pm}0.06^{a}$	$42.8{\pm}0.61^{c}$
2	R1	P_2	$0.74{\pm}0.15^{ab}$	$51.17{\pm}0.55^{ab}$	$0.05{\pm}0.02^{a}$	$5.81{\pm}0.14^{a}$	$42.22{\pm}0.61^{abc}$
3		P_5	$0.56{\pm}0.16^{a}$	$51.03{\pm}0.79^{ab}$	$0.11{\pm}0.06^{b}$	$5.86{\pm}0.06^{a}$	$42.45{\pm}0.95^{bc}$
4		P_0	$0.81{\pm}0.09^{b}$	$50.97{\pm}0.54^{ab}$	$0.06{\pm}0.03^{ab}$	$5.85{\pm}0.07^{a}$	$42.31{\pm}0.64^{abc}$
5	S	P_2	$0.8{\pm}0.14^{b}$	$50.96{\pm}0.67^{a}$	$0.07{\pm}0.02^{ab}$	$5.76{\pm}0.28^{a}$	$42.41{\pm}0.69^{abc}$
6		P_5	$0.76{\pm}0.07^{ab}$	$50.87{\pm}0.8^{a}$	$0.07{\pm}0.03^{ab}$	$5.81{\pm}0.08^{a}$	$42.49{\pm}0.88^{bc}$
7		P_0	$0.75{\pm}0.18^{ab}$	$51.52{\pm}0.17^{ab}$	$0.06{\pm}0.03^{ab}$	$5.92{\pm}0.04^{a}$	$41.74{\pm}0.28^{ab}$
8	R2	P_2	$0.71{\pm}0.1^{ab}$	$51.54{\pm}0.18^{ab}$	$0.06{\pm}0.02^{a}$	$5.91{\pm}0.01^{a}$	$41.79{\pm}0.15^{ab}$
9		P_5	$0.75{\pm}0.15^{ab}$	$51.79{\pm}0.09^{b}$	$0.06{\pm}0.01^{ab}$	$5.91{\pm}0.06^{a}$	$41.5{\pm}0.21^{a}$
Significance			*	*	**	n.s.	*
Min			0.56	50.80	0.05	5.76	41.50
Max			0.81	51.79	0.11	5.92	42.80
Average			0.72	51.18	0.06	5.84	42.19

R1 - Rhizomes of the *Croatian* genotype; R2 - Rhizomes of the *English* genotype; S - seedlings of the *Polish* genotype; P_0= Ash fertilization treatment (0 t/ha); P_2= Ash fertilization treatment (2 t/ha); P_5= Ash fertilization treatment (5 t/ha); Different letters (in columns) indicate difference according to Tukey HSD post hoc test ($p \leq 0.05$); Statistical significance; * $p \leq 0.01$; ** $p \leq 0.05$.

The analysis of the main components of the ultimate analysis variable is shown in figure 2.

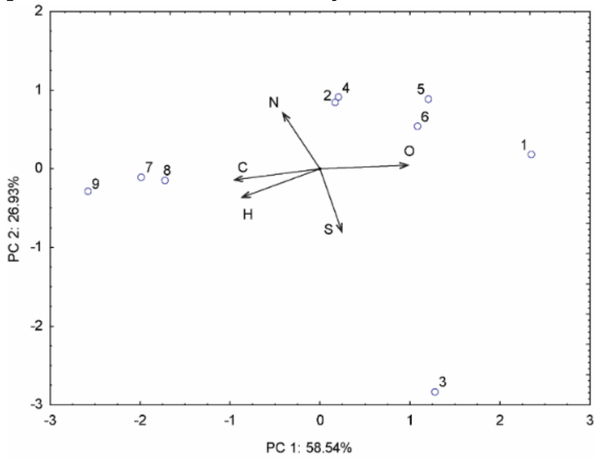

Figure 2. Prinicipal component analysis (PCA) of ultimate analysis

3.3. Proximate analysis and calorific values

Table 2 shows the results of a study that examined the effects of different treatments (P_0, P_2, P_5) on three different types of plants (R1, S, R2), assessing proximate analysis and calorific values.

Table 2. Proximate analysis and calorific values of studied biomass of different *Miscanthus x Giganteus* in relation to different planting material and ash treatment

No.	Planting type	Treatment	Ash (%)	Coke (%)	FC (%)	VM (%)	HHV (MJ/kg)	LHV (MJ/kg)
1		P_0	1.7±0.09^{a}	12.97±0.43^{ab}	10.12±0.41^{a}	79.35±0.62^{b}	18.21±0.34^{a}	16.95±0.33^{a}
2	R1	P_2	1.79±0.09^{ab}	12.21±1.11^{a}	9.34±0.88^{a}	80.06±1.55^{b}	18.42±0.29^{ab}	17.15±0.27^{b}
3		P_5	2.1±0.11^{c}	14.48±2.8^{b}	9.7±0.92^{a}	70.52±13.36^{a}	18.2±0.25^{a}	16.92±0.24^{a}
4		P_0	1.98±0.31^{abc}	13.2±0.57^{ab}	10.08±0.63^{a}	79.3±0.7^{b}	18.29±0.3^{ab}	17.01±0.29^{ab}
5	S	P_2	2.01±0.09^{bc}	13.23±0.54^{ab}	10.03±0.51^{a}	79.01±0.79^{b}	18.28±0.27^{ab}	17.02±0.28^{ab}
6		P_5	2.25±0.38^{c}	12.62±0.98^{ab}	9.21±1.28^{a}	79.36±0.74^{b}	18.11±0.26^{a}	16.84±0.25^{a}
7		P_0	1.81±0.16^{ab}	12.83±0.41^{ab}	9.86±0.46^{a}	79.25±0.29^{b}	18.46±0.22^{ab}	17.16±0.21^{ab}
8	R2	P_2	1.8±0.06^{ab}	12.65±0.84^{ab}	9.75±0.76^{a}	79.83±0.94^{b}	18.28±0.16^{ab}	17±0.16^{ab}
9		P_5	1.78±0.12^{ab}	12.28±1.32^{a}	9.41±1.13^{a}	79.91±1.25^{b}	18.64±0.08^{b}	17.35±0.08^{b}
Significance			*	**	n.s.	*	*	*
Minimum			1.70	12.21	9.21	70.52	18.11	16.84
Maximum			2.25	14.48	10.12	80.06	18.64	17.35
Average			1.91	12.94	9.72	78.51	18.32	17.04

R1 - Rhizomes of the *Croatian* genotype; R2 - Rhizomes of the *English* genotype; S - seedlings of the *Polish* genotype; P_0= Ash fertilization treatment (0 t/ha); P_2= Ash fertilization treatment (2 t/ha); P_5= Ash fertilization treatment (5 t/ha); Different letters (in columns) indicate difference according to Tukey HSD post hoc test ($p \leq 0.05$); Statistical significance; * $p \leq 0.01$; ** $p \leq 0.05$.

Principal component analysis (PCA) of proximate analysis and calorific values for *Miscanthus x Giganteus* is shown in the figure 3.

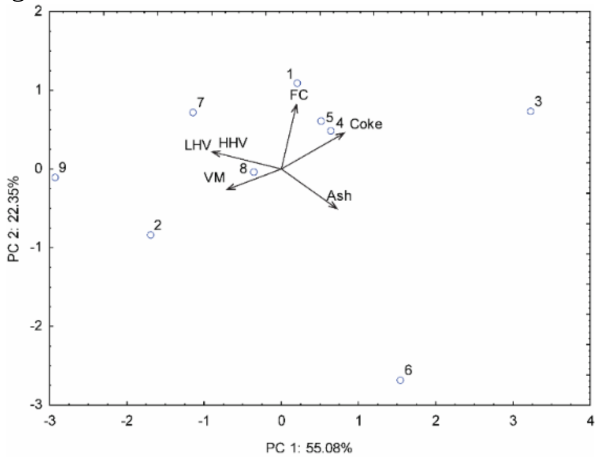

Figure 3. Prinicipal component analysis (PCA) of proximate analysis and calorific values of *Miscanthus x Giganteus*

3.4. Effect of planting material and treatment on changes in the biomass composition of Miscanthus

To study the influence of the parameters of planting type, ash treatment and their interactions on the composition and energy value of biomass, a univariate analysis with the values of the sum of squares for each variable and their statistical significance according to the p coefficient is presented in Table 3.

Table 3. Univariate analysis of the influence of the parameters type of planting material, ash treatment and their interactions on the change in biomass properties *Miscanthus x Giganteus*.

		SoS										
Effect	Df	Ash	Coke	FC	VM	N	C	S	H	O	HHV	LHV
Type	2	1.22*	5.67	0.13	143.88**	0.39*	7.61*	0.00	0.18*	10.82*	0.82*	0.67*
Treatment	2	0.69*	2.65	4.54**	149.99**	0.05	0.29	0.01**	0.01	0.36	0.00	0.01
Type × Treatment	4	0.49**	24.74*	3.47	361.99*	0.15	0.78	0.01**	0.05	1.74	1.02*	1.03*
Error	72	2.56	107.67	49.28	1483.83	1.40	21.40	0.07	1.00	27.43	4.58	4.38

SoS – Sum of squares; Df – Degrees of freedom; FC – content of fixed carbon; VM – content of volatile matter; N – content of nitrogen; C – content of carbon; S – content of sulfur; H – content of hydrogen; O – content of oxygen; HHV – HHV; LHV – lower heating value; Statistical significance; * $p \leq 0.01$; ** $p \leq 0.05$.

3.5. *Modelling the heating value of biomass*

Tables 4 and 5 show the basic characteristics and performance of the developed models

Table 4. Basic information about the performance of the developed regression model

	Performance		Model error				Activation function	
Output	Train	Test	Train	Test	Train algorithm	Error function	Hidden	Output
HHV	0.999	0.999	0.001	0.002	BFGS 8043	SOS	Tanh	Exp.
LHV	0.972	0.999	0.001	0.004	BFGS 0	SOS	Log.	Iden.

Table 5. Statistical error test and residual analysis of the developed regression models

Model	Output	X^2	RMSE	MBE	MPE	SSE	AARD	R^2	Skew	Kurt	StDev	Var
rNN	*HHV*	0.001	0.032	-0.010	0.063	0.008	0.102	0.964	-2.963	8.846	0.032	0.001
	LHV	0.002	0.043	-0.014	0.152	0.015	0.471	0.927	-1.887	4.951	0.043	0.002

rNN – regression neural network; *HHV* – HHV; *LHV* – lower heating value; X^2- chi squared test; RMSE – root mean square error; MBE – mean bias error; MPE – mean percentage error; SSE – sum squared error; AARD – average absolute relative deviation; R^2 – coefficient of determination; Skew – skewness; Kurt – kurtosis; SD – standard deviation; Var – variance

The rNN regression models for predicting *HHV* and *LHV* show robust performance. Prominent indicators include remarkably low chi-squared (X^2) values (0.001 for *HHV*, 0.002 for *LHV*) and substantial coefficients of determination (R^2 = 0.964 for *HHV*, 0.927 for *LHV*).

After conducting Yoon's sensitivity analysis to determine the relative importance of the input variables on the output values of *HHV* and *LHV*, the influence of each variable of the ultimate analysis on the output value was determined (Figure 4).

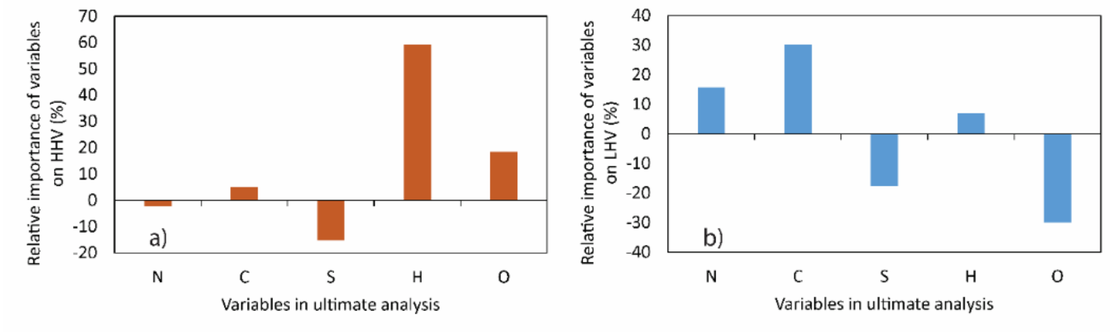

Figure 4. Relative importance (%) of ultimate analysis on the output value of a) *HHV* and b) *LHV*

4. Discussion

The average DM value of the tested samples was 21 t/h, while the average stem height was 3.10 m. In general, ash provides plants with vital substances that can improve plant metabolism, promote root development and improve plant health. The use of ash as fertiliser can increase both fresh mass and dry mass yield of the plants [40]. With regard to the results, it can be seen that the application of R2 in interaction with P_5 had the greatest effect on stem height and was significantly above the average (3.34 m). Šurić et al. (2022) [41] found in their study that the use of sewage sludge as fertiliser increased the yield of the energy crop Virginia mallow. The application of 6.64 t/h sewage sludge increased the average stem height and dry matter yield from 3.12 m; 6.53 t/ ha to 3.28 m; 8.85 t/ha, compared to the control treatment. The two-year study conducted by Saletnik et al., (2018) [42] showed an 8-68% increase in energy crop yields when biochar, biomass ash and their combination are used as soil amendments to replace classical mineral fertilisers and reinforce organic practises. To determine the properties of the input raw material in the production process, it was necessary to study the physico-chemical and chemical properties of the biomass [43]. The highest proportion of C (51.79%) and H (5.92%) was found in R2 rhizomes in all fertiliser treatments. Voća et al (2021) [44] reported the values for elements of the ultimate analysis *Miscanthus x Giganteus* for C (51.65%), H (6.09%), N (0.18%), S (0.08%), O (42.00%) after laboratory analysis. When comparing the results of the analysis, it was found that the values obtained were within the range of the literature researched. The lowest sulphur content (0.05%) was found when rhizomes from Croatia (R1) were used, i.e. when no ash was used (P_0). Considering the negative impact of sulphur on the environment, it is recommended to use fuel with a lower sulphur content [45]. Anshariah et al., (2020) [46] states that there is a strong correlation between the proportion of FC and the increase in calorific value, i.e. that the increase in FC directly affects the increase in energy values. Although in the study the highest proportion of FC (10.12%) shows that R1 without applying any fertiliser treatment does not have the highest calorific value and is even lower than the average (18.21 MJ/kg), which is also influenced by other variables in the proximate analysis [47]. The highest ash content was found in plant type 'S' under treatment P_5 (2.25%). Gismatulina et al., (2022) [49] gives ash values in the range of 0.90-2.95%. The highest HHV and LHV values (18.64; 17.35 MJ/kg) were found in R2 with the P_5 treatment of ash fertilisation (5 tonnes per hectare). Significant differences were found in VM content between samples, which reached a maximum of 80.06% in R1 plant after P_2 treatment. This result highlights the significant influence of plant type and treatment on critical properties of the plant material, which has potential implications for energy production and various industrial applications. Šurić et al. (2022) [41] reported that no significant differences in ash, coke, fixed carbon and calorific value were found after the application of different sewage sludge fertiliser treatments. However, the application of sewage sludge treatment at a rate of 1.66 t/h resulted in a significant increase in VM. Osman et al. (2018) [50] reported a volatile matter (VM) value of 72.5% and ash content of 3.38% after analysis. The study by Yorgun and Şimşek (2003) [51] reported a biomass composition of 71.4% volatile matter, 18.5% solid carbon, 3.3% ash and 6.8% moisture.

In the final step of the study, an artificial neural network regression model was developed to model the HHV of biomass *Miscanthus x Giganteus*.

When validating the regression neural network (rNN) model, the data was split as standard into 70% for training and 30% for testing to ensure a comprehensive assessment of the models predictive accuracy. The robustness of the model was confirmed by various statistical error tests and residual analyses, including the chi-square test, root mean square error (RMSE) and coefficient of determination (R^2), demonstrating its effectiveness in predicting the higher and lower heating values (HHV and LHV) of *Miscanthus x Giganteus* biomass.

The model used to estimate the HHV showed better performance in training and testing (0.999 and 0.999) in contrast to the model used to estimate the LHV (0.972 and 0.999). Comparing the predictive performance of the rNN model developed in this study with that reported by Noushabadi et al. (2021) [52], a number of observations become clear. The coefficient of determination (R^2) achieved by the rNN model for HHV (0.964) and LHV (0.927) indicates a better fit to the data than the maximum R^2 of 0.96.

The study limitations include a limited sample size and diversity, focusing on specific *Miscanthus x Giganteus* species and ash fertilisation treatments. Its regional focus may not fully represent the different geographical contexts. Future research should investigate how different climates and soils affect *Miscanthus x Giganteus*, assess the long-term environmental impacts of ash fertilisation, and use advanced technologies to better understand plant-environment interactions. These steps are critical to understanding the plant's role in sustainable biomass production and its environmental impact.

5. Conclusions

In this study of *Miscanthus x Giganteus*, different planting materials and ash fertilizers were found to have different effects on crop yields, growth, and composition. Notably, sample 3 had the highest yield, sample 8 had the lowest yield, and sample 9 had exceptional development with the greatest average stem height. Unfertilized seedlings had elevated nitrogen levels, while R1 types had low sulphur levels under certain conditions. Ash formation was notable in 'S' x P5 plants, while R1 x P5 combinations had high carbon content as evidenced by high coke levels. Energy content, as measured by HHV and LHV, varied in all cases, illustrating the effects of treatments. The artificial neural network (ANN) regression model showed high efficiency in predicting the higher heating value (HHV) and lower heating value (LHV) of *Miscanthus x Giganteus*. The model showed excellent performance metrics with robust coefficients of determination, indicating its potential as a reliable tool for estimating the energy content of biomass.Acknowledgement

The publication was supported by the Croatian Science Foundation, under project No. IP-2018-01-7472 “Sludge management via energy crops production” within the project “Young Researchers’ Career Development Project—Training of Doctoral Students”, and co-financed by the European Union, under the OP “Efficient Human Resources 2014–2020” from the ESF funds.

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Submitted: 07.11.2023
Revised: 02.01.2024
Accepted: 15.01.2024