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Can wood waste be a feedstock for anaerobic digestion? A machine learning assisted *meta*-analysis

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ABSTRACT

Anaerobic digestion is widely employed to process various organic wastes while generating renewable energy and nutrient-rich digestate. However, lignocellulosic wastes, especially wood waste, suffer from the recalcitrance associated with high lignin content, thereby adversely impacting on biogas production. It remains unclear whether wood waste is suitable as a feedstock for anaerobic digestion and to what extent pretreatment techniques could affect its biochemical methane potential. In this paper, 769 datasets on methane production from wood waste were collected for *meta*-analysis. The results showed an average 146 % increase in methane production for other organic wastes compared to wood waste when pretreatment techniques were not applied, but this gap could be mitigated to 99 % when pretreatment techniques were considered, indicating that pretreatment techniques could be more effective for wood waste. A further analysis of different pretreatment techniques showed that pretreatment significantly increased the methane production of wood waste by 113 % and that a combination of pretreatment techniques was more effective than a single method. Finally, three machine learning algorithms were applied to explore the relationship between methane production and selected variables. The results showed that the random forest method yielded better predictive performance for methane production ($R^2 = 0.9643$) than artificial neural networks and support vector regression. Feature importance analysis found that particle size had a higher influence than temperature or feedstock composition. Overall, this study gives insight into the potential of utilizing wood waste as a feedstock for anaerobic digestion and the importance of employing suitable pretreatment methods. This work also reveals correlations between methane production and critical variables, which could serve as a guide for optimizing operational adjustments during anaerobic digestion.

1. Introduction

The world is currently in transition from a fossil energy economy system to an era of renewable and sustainable resource availability [1]. Trees, as the most abundant sustainable bioresource, not only serve as a versatile building material but also as a source of bioenergy, attracting considerable attention in this epochal transformation [2]. The world's total growing stock of trees was about 5.57E11 m^3 in 2020, and it is estimated that approximately 3.97E09 m^3 of wood were harvested in 2018 [3]. A substantial amount of wood waste is generated from different sources throughout the timber supply chain, such as logging operations [4], sawmills [5], furniture manufacturers [6], pruning activities [7], and construction and demolition [8]. In general, almost 50 % of a tree can be processed to the saleable product, while the rest is retained as wood waste [9]. However, due to a combination of factors only a limited amount of wood waste has been available for recycling and reuse.

Wood is often subject to surface treatment prior to use and therefore post-consumer wood may contain various impurities and contaminants. Such treatments can be environmentally harmful if proper disposal and further processing are not carried out. To help ensure proper disposal and a sustainable recycling of wood waste, the Wood Recyclers Association in UK has divided post-consumer wood into 4 categories [10]: Grade A being visibly clean and chemically untreated; Grade B being chemically treated but non-hazardous industrial wood waste; Grade C being chemically treated but non-hazardous municipal wood waste; Grade D being chemically treated and hazardous. Currently, whilst only grade A should be recycled and reused, it is commonly recycled together with a mixture of B and C [11]. Conventional approaches to dealing with wood waste include recycling, sanitary landfill, and incineration.

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Although these practices have been widely adopted with government support (e.g., subsidies and policies), they significantly limit the potential to exploit the resources embedded in wood waste. In addition, landfill can cause environmental problems by releasing large amounts of greenhouse gases [12,13]. The widescale recycling of wood waste is strongly limited in practice by factors such as waste collection and transportation, environmental regulations and the development level of a particular country [14]. The emission of harmful compounds on the combustion of chemically treated wood waste on a large-scale is also problematic [15,16]. The combination of all these factors underlines the urgent need for alternative waste management strategies that can reduce the environmental impact of wood waste and tap into its value as a sustainable bioresource.

Anaerobic digestion (AD) is an appealing option that simultaneously helps to mitigate pollution caused by improper wood waste treatment and generates biogas, a source of renewable energy. AD can be used not only to manage wood waste from mushroom cultivation [17], forest residues [18], municipal solid waste [19], yard trimmings [20], and wood processing [21], but also wood waste treated with chemical preservatives or contaminated with toxic compounds. For example, Ali et al. have constructed multiple microbial consortia that can be used to enhance the biochemical methane potential (BMP) of creosote-treated wood [22,23]; Evandro et al. performed AD using arsenic-rich *Pteris vittata* and found that AD was effective in removing arsenic with methane production reduced by only 7 % compared to control group [24]. In addition, part of the organic matter from industrial biogas plants remains in the solid phase of the digestate, which can then be separated out and used as soil conditioner [25] or as pyrolysis feedstock to yield gas, bio-oil and biochar [26,27]. However, the high lignin content and recalcitrant crystalline cellulose structure of wood waste make efficient and timely biogas production difficult, which limits their large-scale application in AD [28]. Although many pretreatment techniques to enhance the biogas production of wood waste have been developed by the reduction of particle size, the improvement of lignocellulose biodegradation, or the removal of any inhibitors and toxic compounds [29–31] landfill and incineration treatment remain commonplace while AD is often overlooked. To the best our knowledge, no systematic analysis has been published to discover the potential of wood waste as feedstocks in AD. Meta-analysis, a scientific statistical method, is ideally suited for bridging the gap between traditional literature review and quantitative analysis [32]. By analyzing a large amount of data, more dependable conclusions can be drawn [33]. Thus, systematic employment of *meta*-analysis allows for the acquisition of reliable conclusions. Furthermore, Machine learning (ML) is a tool with the capability of developing predictive models by extracting internal information and learning patterns from large data sets [34]. There is therefore the potential that a refined ML model can be used to calibrate system parameters to optimize biogas output.

This study employs a hierarchical *meta*-analysis approach to analyze BMP of wood waste, including the comparison between BMP of wood waste and other organic wastes and the enhancement of different pretreatment techniques on BMP of wood waste. Then, the effects of different parameters in AD of wood waste were determined through diverse ML algorithms. The chief goals of this research were to (i) investigate the BMP of wood waste and other organic wastes; (ii) identify the pretreatment techniques that significantly improve BMP of wood waste; (iii) confirm the main factors affecting methane production and optimize the AD conditions; (iv) predict methane production from substrate physicochemical characteristics and AD conditions for industrial applications.

2. Materials and methods

2.1. Literature search and data selection

The literature search was conducted by two separate individuals according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, in the databases Web of Science and PubMed that combined keywords related to AD with keywords related to wood waste (cutoff date 07 December 2022). The following search terms were employed: (anaerobic *digestion OR biogas OR biomethane) and (lignocellulos* OR wood* OR forest* OR sawdust*), and searches in Web of Science were limited to the topic [title/abstract/keywords] and in PubMed to [title/abstract]. A total of 4441 articles (excluding duplicates) were initially obtained, then the title and abstract were examined and finally the full manuscripts (Fig. B.1). Publications included in this *meta*-analysis were considered to meet the following criteria: (1) investigated wood wastes as feedstocks for AD; (2) studies with "treatment" group and "control" group, where other experimental conditions were identical; (3) included methane production in a standard format (L kg^{-1} of volatile solid (VS) or L kg^{-1} of total solid); and (4) measurable data were presented for the determination of mean value and uncertainty of methane production, as standard deviation (SD) or standard error (SE). Subsequently, 42 publications were retained in the *meta*-analysis containing 259 groups of datasets on different pretreatment methods for wood waste, 22 groups of datasets on anaerobic co-digestion of wood waste, and 488 groups of datasets on comparing wood waste with other organic wastes in AD (Table A.1-A.2).

Moreover, publications included in the machine learning analysis were considered to meet the following criteria: (1) investigated wood wastes as the feedstocks for AD; (2) included methane production in a standard format (L kg^{-1} of VS); (3) presented measurable data for the determination of mean value and uncertainty of BMP, as standard deviation (SD) or standard error (SE); (4) detailed lignocellulosic component of wood wastes; and (5) presented details on inoculum, volume, temperature and the ratio of inoculum to substrate in AD. To form a qualified dataset, nine input variables including wood types, inoculum types, volume (ml), temperature (℃), particle size (mm), ratio of inoculum to substrate (based on VS), cellulose content (%), hemicellulose content (%), lignin content (%), and digestion time (d) were chosen, in which wood types and inoculum types were represented as categorical objects. The accumulated methane production (L kg^{-1} of VS) during AD was selected as the output variable. To avoid bias introduced by imputation, publications lacking any of the above information were not considered. Under these criteria, 1179 groups of datasets were collected from 19 publications for this machine learning analysis (Table A.3). The values of numerical objects were extracted manually using the WebPlotDigitizer (https://automeris.io/WebPlotDigitizer/, Version 4.6).

2.2. Meta-analysis

Three essential parameters for the methane production were extracted from the screened papers, including the mean, standard deviation (SD), and the number of replicates (n). If standard errors (SE) was provided, the SD can be calculated using formula SD = SE * sqrt (n). For the *meta*-analysis, a natural log-transformed response ratio is used as a metric to estimate the magnitude of the treatment effect, with the detailed methodology described in previous publications [35,36].

A subgroup *meta*-analysis was conducted to compare the BMP of wood waste with other organic wastes and to explore the impact of different pretreatment methods on BMP of wood waste. The types of wood waste were classified into hardwood and softwood; the pretreatment methods included biological techniques, chemical techniques, physical techniques, anaerobic co-digestion techniques, and combination of multiple methods; other organic wastes included crop straw, municipal solid waste, wild plant, and yard waste. Meta-analysis was conducted using the "metafor" package and "forestplot" package, implemented in R version 4.1.3 (https://www.r-project.org/). This study used and modified the codes from Zhang et al. [36], and detailed description of the codes are available in the repository: https://github.com/pablogalaviz/Micro-Plastics-Meta-Analysis.git.

2.3. Implementation of ML models

Three types of supervised ML models, namely support vector regression (SVR) [37], random forest (RF) [38,39], and artificial neural networks (ANN) [40], were selected to simulate the complex effects of AD parameters on BMP of wood waste, as all three have been found to be accurate in predicting methane production [41]. In the process of constructing reliable models, 80 % of datasets were used for training and 20 % reserved for testing. Prior to model training, the data was normalized to eliminate issues associated with dimensions and units [42].

In the SVR modelling, kernel functions remap the constrained dimensional space into a more expansive one. The SVR problem is resolved by minimizing the values of the loss function and simultaneously maximizing the margin [43]. To optimize the preliminary trained model, a cross-validation based grid search was employed on hyperparameters, followed by the function selection.

The RF model is an ensemble modelling algorithm developed based on decision tree algorithms. The incorporation of random sampling and ensemble strategies in RF facilitates precise predictions and assists in circumventing overfitting. It is imperative to consider hyperparameter tuning when designing an optimal tree structure, with the principal parameters being adjusted based on cross-validation.

ANNs are mathematical frameworks designed to replicate the neural systems of the human brain, processing information through a weighted sum of inputs. The back-propagation neural network was utilized in this paper; the network error is transferred from the output layer to the input layer to adjust the network's weights and biases. In the pursuit of an efficient neural network, a selection of activation functions and the number of hidden nodes were explored.

3. Results and discussion

3.1. Overview of studies of impact of AD on wood waste

Initially, 42 research articles were identified from the literature search results which experimentally investigated BMP of wood waste. The number of publications referencing AD has increased annually, with significant growth since 2006. Although AD has received increasing interest, there are few publications exploring AD of wood waste, with the number basically stable at four per year since the first publication in 2010 (Fig. 1a). The search results about AD were divided into two categories. The first is ethanol fermentation, where the main feedstocks investigated are crop straws (agricultural wastes); the other part is where the main feedstocks are manure, food waste, and sludge (Fig. 1b). Whilst AD requires microorganisms to metabolise organic matter into useful products the complex structure of lignocellulosic wastes contains bonds and functional groups that make their degradation very difficult [28]. In contrast, the organic matters of manure, food waste, and sludge are more amenable to AD as subsequently have become a greater focus of research [44,45].

From the selected 42 studies, a total of 769 datasets were identified and were mainly classified by comparing different pretreatment methods and different organic wastes. Fig. 1c shows the respective proportion of each research content, where other organic wastes include

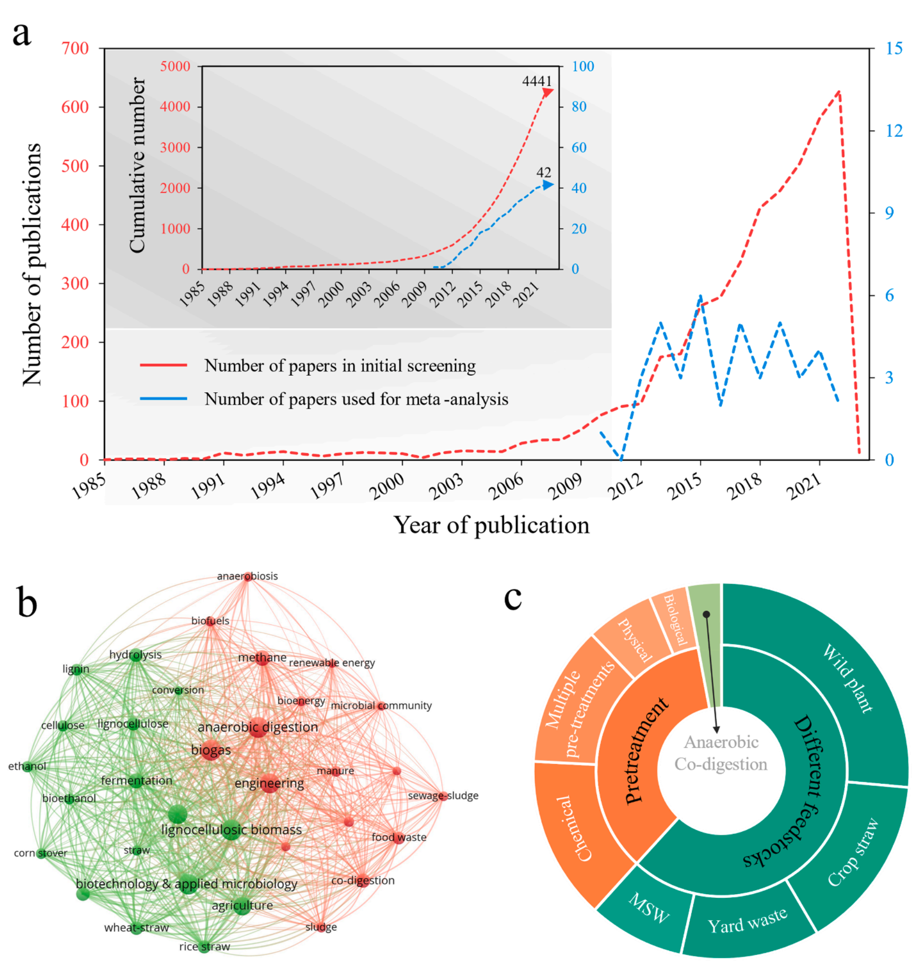

Fig. 1. General trends in experimental research about the anaerobic digestion of wood waste. (a) Number of publications before 07 December 2022 that experimentally examined the anaerobic digestion of wood waste. (b) Keywords co-occurrence analysis, plotted by VOSviewer 1.6.18 software. (c) Respective proportion of research content (n = 769), including pretreatment techniques (n = 281) and the type of other organic waste (n = 488). MSW: Municipal solid waste.

wild plant (42.73 %), crop straw (24.45 %), yard waste (19.38 %), and municipal solid waste (13.44 %). 22 groups of datasets concerned the anaerobic co-digestion of wood waste with other wastes, such as manure, food waste, crop straw, showing that anaerobic co-digestion can increase BMP by 199.23 % (Table A.2). Furthermore, the maximum increase occurred when woodchips and food waste were anaerobic co-digested in a 1:1 wt ratio [46]. Fig. B.2 shows wood waste had the lowest BMP compared to other organic wastes, which could be explained by the high lignin content in the wood waste [28]. Yard waste consisted mainly of leaves, grass clippings, flowers, twigs, and branches, and twigs and branches account for a large part [47]. Therefore, the BMP of yard waste was close to wood waste. Moreover, BMP also differed considerably between softwoods and hardwoods, with hardwoods being more productive. In the subsequent *meta*-analysis, hardwoods and softwoods are considered separately.

3.2. BMP comparison for different organic wastes

For studies considering AD of different organic wastes, the feedstocks involved mainly lignocellulosic wastes, which were classified according to source and variety as wood waste, crop straw, wild plant, yard waste, and the organic fraction of municipal solid waste (Table A.2). Of these, the first four (wood waste, crop straw, wild plant, and yard waste) are all considered lignocellulosic wastes, while municipal solid waste are highly nonhomogeneous mixture generated from residential, commercial, and industrial sectors [48]. Wild plant refers to the natural herbaceous phytomass that grows in the wild without any human intervention [49]. These wastes could partly overlap because of their complexity, for example, municipal solid waste consists of yard trimmings (garden cuttings), which is also divided into yard waste [47,50]. In Fig. 2, the response ratio of other organic wastes compared to wood waste is presented. Summarizing across the organic waste types, wood waste had the lowest BMP. In particular, crop straw BMP was 132 % higher than wood waste, wild plant BMP was 181 % higher, yard waste BMP was 89 % higher, and municipal solid waste BMP was 134 % higher. The summary effect size for other organic wastes in comparison to wood waste was 2.22 [95 % CI: 1.82, 2.72] ($p < 0.001$). This means that on average the BMP of other organic wastes was 112 % higher than that of wood waste. These results were primarily due to the chemical composition of the organic wastes. The cellulose, hemicellulose, and lignin content of crop straw was 40.67 %, 16.87 % and 21.76 % respectively, in addition to 3.12 % water soluble carbohydrate and 4.65 % crude protein [51]; The chemical composition of wild plant in terms of cellulose, hemicellulose and lignin was 45.37 %, 34.33 % and 15.11 % respectively [49]; The cellulose, hemicellulose, and lignin content of yard waste was 39.65 %, 29.35 % and 23.91 % respectively [52]; In municipal solid waste, kitchen waste contained 6–16 % degradable holocellulose, 31–41 % sugars, 17–22 % protein, and 14–25 % fat, and the degradable paper had 72–94 % degradable holocellulose [53]. However, wood waste consisted of 31.07 % cellulose, 17.12 % hemicellulose, and a high lignin content (28.82 %) [28]. Lignin is the major component of the recalcitrant fraction of lignocellulosic waste and an important factor limiting their BMP [54,55]. The overall improvement in BMP of hardwood waste was 83 % compared to softwood waste with summary effect size of 1.83 [0.96, 3.49] ($p = 0.0669$) (Fig. 2). Furthermore, a similar trend was observed when other wastes compared to hardwood and softwood respectively. This could be explained by the high content of polysaccharides in hardwood and the lower lignin content [56]. On the other hand, the hardwood xylan had a higher degree of deacetylation, making them more susceptible to degradation [57].

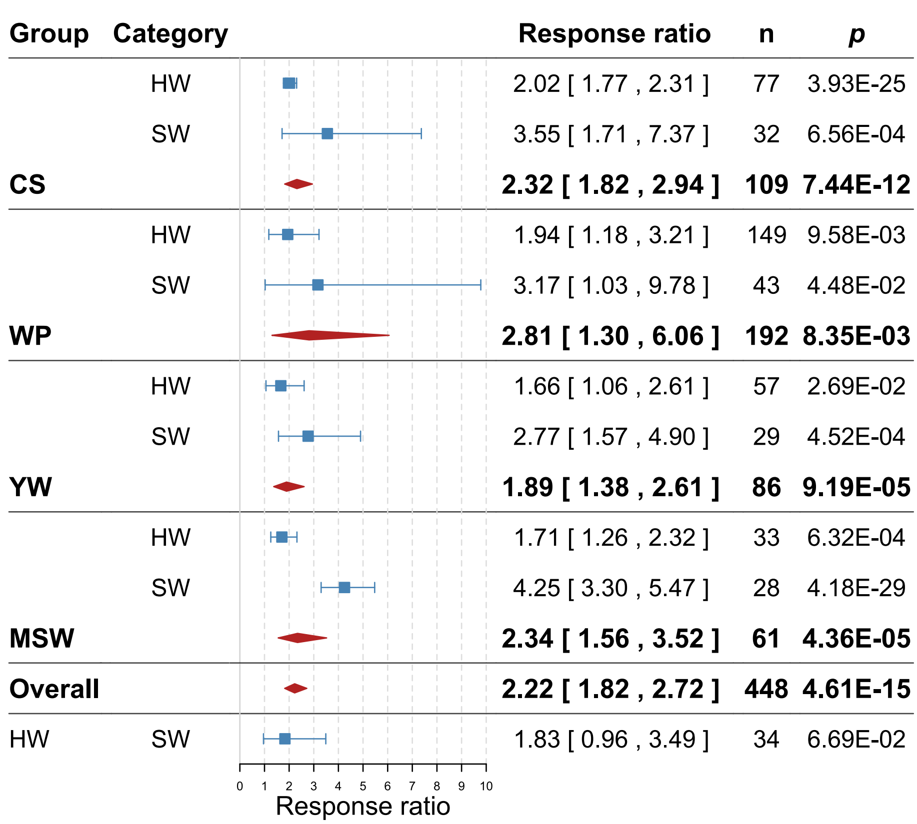

Fig. 2. The response ratio of methane production from other organic wastes compared to wood waste. The blue square symbols show mean effect size with error bars representing 95 % confidence interval, and the red diamond represents the summary effect. A ratio > 1 indicates that the methane production from the treatment is higher than that from the control group, and specifically, a response ratio of 2.22 indicates that the treatment group produces 122 % higher methane compared to the control group. n refers to sample size, and *p* means the *p*-value of the Q test with $p < 0.05$ indicating a significant difference. HW: Hardwood; SW: Softwood; CS: crop straw; WP: wild plant; YW: yard waste; MSW: municipal solid waste.

To investigate the impact pretreatment has on BMP, the dataset was divided into two parts, with and without pretreatment, for analysis. In the absence of pretreatment for substrates, the overall BMP of other organic wastes was 146 % higher than wood waste with summary effect size of 2.46 [1.89, 3.19] ($p < 0.001$). However, this gap was reduced to 99 % with summary effect size of 1.99 [1.59, 2.48] ($p < 0.001$) under the application of pretreatment techniques (Fig. 3). The results showed that wood waste specifically had better pretreatment potential — pretreatment increased its BMP by a greater amount — than for other organic wastes. Pretreatment techniques can change the chemical structure of lignin, making it more accessible to microorganisms, which greatly increased the BMP of wood waste [58]. Additionally, the BMP of municipal solid waste fluctuated considerably (Fig. 3c and 3d), as the composition of municipal solid waste varied significantly among different geographical areas. For example, the municipal solid waste investigated by Krause et al. consisted of mainly paper and paperboard [19], yet Pastor-Poquet et al. focused on MSW consisting of household waste, restaurant waste, and spent coffee [59].

3.3. Response of BMP to pretreatment techniques on wood waste

A number of studies have shown that pretreatment techniques can enhance BMP of lignocellulosic wastes by increasing the surface area of feedstock (size reduction and the wetting of biomass) and biomass decrystallization, resulting in an increase in the accessibility and biodegradability of microorganisms to the organic matter [23,60,61]. However, it is still not fully clear to what extent pretreatment techniques contribute to the BMP of wood waste and how to choose the optimal pretreatment technique for different sources and components of wood waste. The cumulative methane production of wood waste after different pretreatment techniques is shown in Fig. B.3. According to the *meta*-analysis depicted in Fig. 4, the employment of pretreatment strategies significantly improved the BMP of wood waste by 113 % (n = 250), with an overall effect size of 2.13 [1.68, 2.70] ($p < 0.001$). Furthermore, the combination of multiple pretreatment techniques was more effective than a single approach, except for the combination of biological and chemical strategies (86 %, n = 39) which was slightly less effective than physical strategy (99 %, n = 43). Many studies have demonstrated that a combination of two pretreatments, like biological with chemical or physical strategies, was more useful compared to a strategy alone [62]. An appropriate combined strategy would not only improve the decomposition of lignocellulosic feedstocks, but also optimize the utilization of their constituent components, all while keeping operating costs relatively low and optimising the product quality [63]. The synergistic impact of combining physical pretreatment with either chemical or biological pretreatments was observed to markedly enhance the BMP, with effect size of 4.76 [1.98, 11.44] ($p < 0.001$) or 4.67 [2.10, 10.39] ($p < 0.001$) respectively (Fig. 4). These findings imply that physical pretreatment plays a pivotal role in facilitating successful AD of wood waste, underscoring the necessity of employing multiple pretreatment strategies to maximize the BMP of woody biomass. The summary effect size of hardwood and softwood were 1.85 [1.49, 2.29] ($p < 0.001$) and 2.55 [1.60, 4.04] ($p < 0.001$), and akin to the outcomes on all wood waste, physical pretreatment and multiple pretreatment strategies were exceedingly advantageous in advancing the BMP (Fig. B.4). It is noted that in some specific cases that combine pretreatment did not result in higher BMP values in comparison to single pretreatment.

The largest increase in the methane yield for wood waste was observed after the combination of biological and physical pretreatments (Table 1). Hydrothermal treatment together with cellulolytic enzyme was the method with highest increased BMP (3074.2 %) when compared

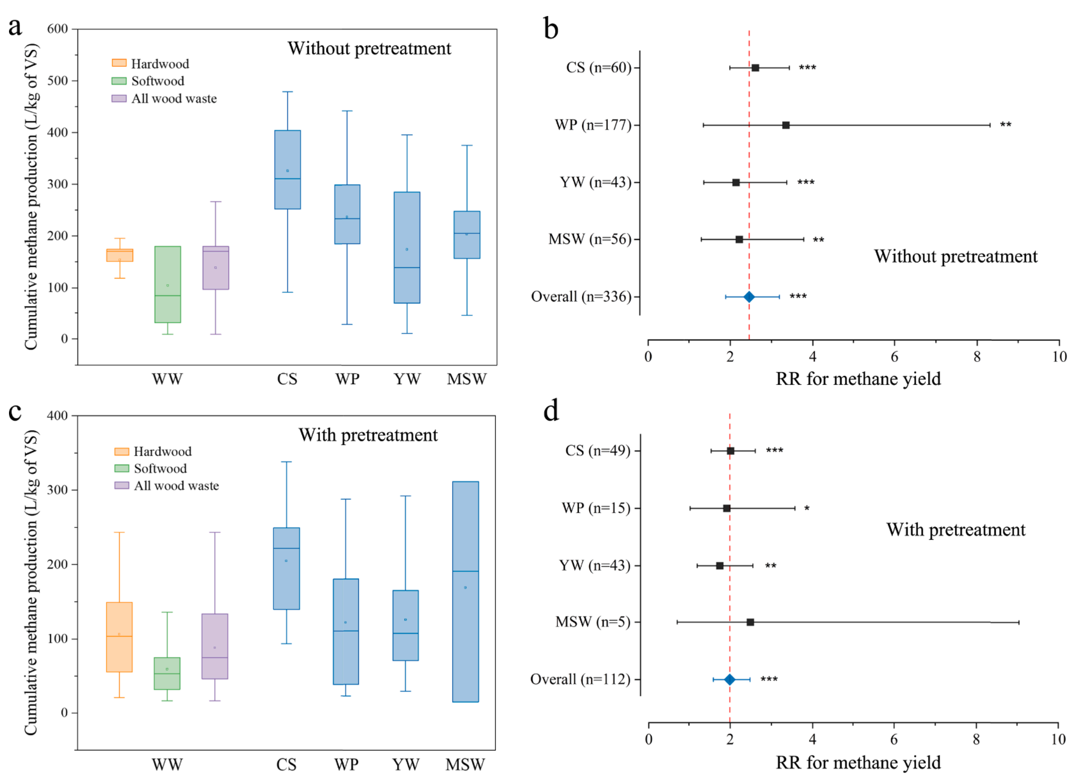

Fig. 3. The cumulative methane production of different organic wastes (a) without pretreatment and (c) with pretreatment techniques. The response ratio of methane production from other organic wastes compared to wood waste (b) without pretreatment and (d) with pretreatment techniques. WW: wood waste; CS: crop straw; WP: wild plant; YW: yard waste; MSW: municipal solid waste. For (b) and (d), the plot shows the mean effect size (black squares and blue diamond) with error bars representing 95 % confidence interval. A ratio > 1 indicates that the methane production from other wastes is higher than wood waste, and specifically, a response ratio of 2.22 indicates that other wastes produce 122 % higher methane compared to wood waste. n refers to sample size and p means the p-value of the Q test, with (*) $p < 0.05$; (**) $p < 0.01$; (***) $p < 0.001$.

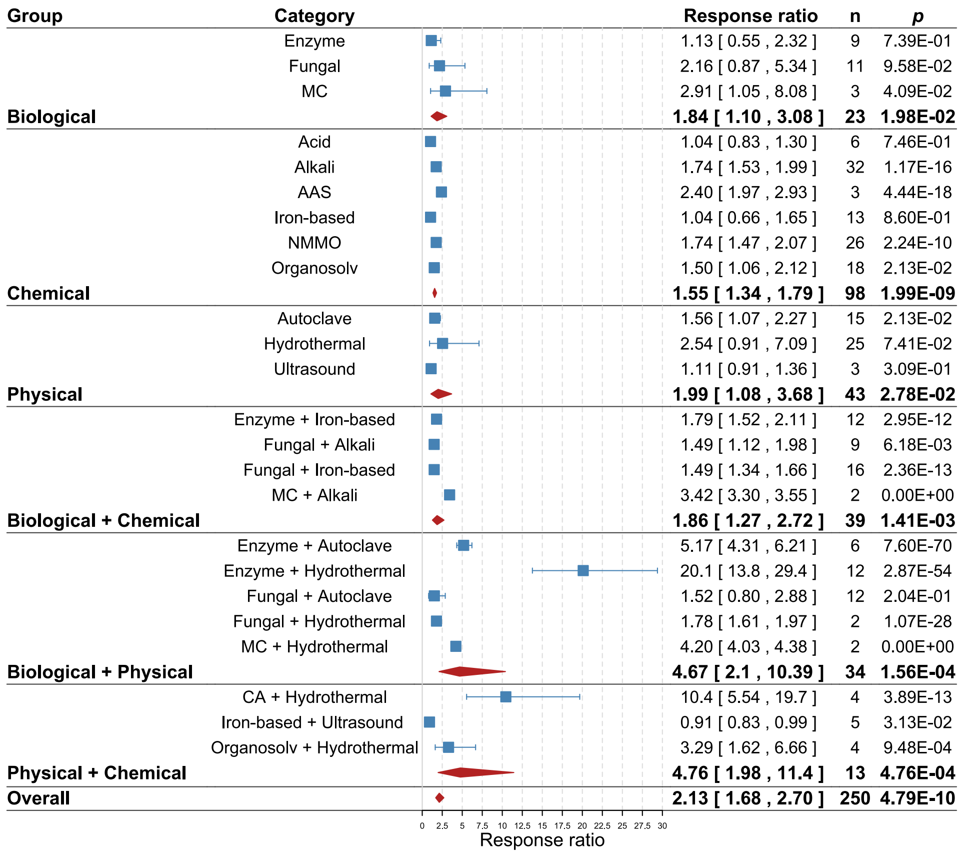

Fig. 4. The effects of different pretreatment techniques on methane production from wood waste. The blue square symbols show mean effect size with error bars representing 95 % confidence interval, and the red diamond represents the summary effect. A ratio > 1 indicates that the methane production from the treatment is higher than that from the control group, and specifically, a response ratio of 2.13 indicates that the treatment group produces 113 % higher methane compared to the control group. n refers to sample size, and *p* means the *p*-value of the Q test with $p < 0.05$ indicating a significant difference. MC: Microbial consortium; AAS: Aqueous ammonia soaking; NMMO: N-methylmorpholine-N-oxide; CA: Chemical antidote.

to untreated wood waste [18]. The process of hydrothermal treatment has been shown to be an effective means of augmenting the solubility of biomass, thereby creating a more conducive environment for enzymatic activity [64]. Additionally, an important factor contributing to the significant improvements in BMP observed in these studies was the markedly low levels of methane production from untreated wood, close to 5 mL/g of VS [18]. Despite the considerable gains in BMP that can be achieved with these pretreatment strategies, it is imperative that a thorough investigation is carried out into the energy consumption and materials associated with these techniques, in order to surpass the cost-benefit threshold in practical applications. Physical techniques tend to be energy intensive, whereas chemical techniques could result in the production of environmentally hazardous substances, and have their own environmental footprints [65]. By contrast, biological techniques, while being a comparatively slower process, are typically economical approaches that require minimal energy input and are largely devoid of hazardous chemicals [28]. Indeed, among individual pretreatment techniques, biological pretreatment exhibited the most substantial increase in BMP relative to physical and chemical pretreatment, registering an impressive 713 % growth (Table 1). Yet, when it comes to wood waste, the research on biological pretreatment and the identification of microbial consortium involved in wood degradation is still in its infancy.

3.4. BMP of wood waste predicted by ML models

3.4.1. Description of the collected datasets for ML

The characteristics of all the variables used for ML are shown in Table A.3. For pretreated wood materials, the properties of materials after pretreatment were provided for analysis. The inoculum could be divided into sewage sludge and effluent from anaerobic digestion of manure, both of which were common types of high-nitrogen inocula (high nitrogen) to balance the typically high carbon to nitrogen ratio of feedstock and enhance the digestion performance [78]; Wood types were divided into hardwood and softwood according to the previous *meta*-analysis results. Although the data collected primarily employed the mesophilic conditions (30–40 ℃), the reaction progressed more rapidly under thermophilic conditions, resulting in higher biogas production rates [79]. The AD of wood waste lacked data on thermophilic conditions. Meanwhile, the data on digestion volumes was also incomplete, as the volumes in the dataset were obtained from lab-scale.

To further reveal insights into the collected datasets, linear correlations between pairwise variables were analysed using Pearson correlation coefficient. As shown in Fig. 5, there was a weak positive correlation between inoculum types and lignin content with methane production. Many parameters, like temperature and I/S ratio, did not present a linear correlation with methane production, while these parameters have been proved to influence the methane production of AD [80,81]. Therefore, further internal relationships between these variables should be discovered based on big data and non-linear methods.

3.4.2. Methane production predicted by ML algorithms

The collected data (except for the methane production data) were processed as input variables for the ML models and the methane production values were considered as output variables. After the parameter optimization process (Fig. B.5 and B.6; Table B.1 and B.2), all three models showed good fitting results, where RF ($R^2 = 0.9643$, RMSE = 15.52) was followed by ANN ($R^2 = 0.9640$, RMSE = 16.30) and SVR (R^2

Table 1
Performance of the pretreatment techniques for wood waste and maximum methane yield increase under specific pretreatment configuration.

Pretreatment	Average methane production (L/kg of VS)			Maximum increase in methane production	
	$\overline{X}_{Control}$	$\overline{X}_{Treated}$	$\overline{X}_{Increase}$ (%)	Specific pretreatment configuration	Maximum increase (%)
Biological					
Enzyme	56.1	66.2	51.7 (n=9)	30 FPU/g cellulolytic enzyme at 50 °C for 12 h [18]	185.4
Fungal	108.0	178.0	178.7 (n=12)	*Ceriporiopsis subvermispora* at 28 °C for 7 days [66]	265.5
MC	44.7	81.1	286.7 (n=3)	Aerobic sludge pretreatment at 37 °C and 90 rpm for 10 d [30]	713.0
Chemical					
Acid	26.4	27.6	6.5 (n=6)	85% phosphoric acid at 60 °C for 45 min [67]	39.8
Alkali	80.5	153.1	101.9 (n=36)	NaOH at -15 °C for 16 h [68]	556.8
AAS	30.8	76.9	150.5 (n=3)	AAS at 22 °C for 3 d [69]	176.9
Iron-based	237.5	297.9	27.3 (n=13)	0.5 mM Fe(II) and H_2O_2 [70]	49.0
NMMO	45.2	85.8	90.1 (n=20)	75% NMMO for 15 h [71]	298.2
Organosolv	54.9	78.4	65.6 (n=18)	Ethanol extractives [72]	319.6
Physical					
Autoclave	79.4	104.0	90.6 (n=15)	Steam explosion at 20 bar for 10 min [73]	669.7
Hydrothermal	42.7	109.8	36.3 (n=17)	Hydrothermal at 170–210 °C for 30 min [74]	258.4
Ultrasound	118.8	117.6	12.0 (n=3)	Ultrasonic at 40 KHz and 40 °C for 30 min [30]	35.7
Biological + Chemical					
Fungal + Iron-based	190.7	279.3	54.8 (n=16)	*Pleurotus ostreatus* at room temperature for six weeks + Fe(III) and H_2O_2 [70]	136.8
Enzyme + Iron-based	190.7	326.1	88.2 (n=12)	0.5 mM Fe(II) and H_2O_2 + Enzyme at 50 °C for 96 h [70]	155.1
Fungal + Alkali	95.4	139.6	46.4 (n=8)	*Abortiporus biennis* at 27 °C for 30 d + NaOH at 80 °C for 24 h [75]	115.0
MC + Alkali	13.6	46.0	237.3 (n=2)	NaOH at room temperature for 10 min + MC [30]	245.2
Biological + Physical					
Enzyme + Autoclave	10.9	56.5	418.5 (n=6)	Steam explosion at 16 bar for 10 min + 30 FPU/g enzyme [73]	491.4
Enzyme + Hydrothermal	8.2	167.9	2069.5 (n=8)	Hydrothermal at 210–215 °C for 5 min + 30 FPU/g cellulolytic enzyme at 50 °C for 12 h [18]	3074.2
Fungal + Autoclave	106.8	159.8	68.0 (n=12)	Steam explosion at 210 °C for 10 min + 2% *Caldicellulosiruptor bescii* culture (v/v) [76]	143.2
Fungal + Hydrothermal	28.9	51.8	79.3 (n=2)	Hydrolysis + *Petronet alfa* [29]	88.6
MC + Hydrothermal	9.6	40.3	319.9 (n=2)	Liquid hot water + MC [30]	320.9
Physical + Chemical					
CA + Hydrothermal	10.6	108.5	972.5 (n=4)	Hydrothermal at 210–215 °C for 5 min + Sodium dithionite as a chemical antidote [18]	1677.1
Iron-based + Ultrasound	341.3	310.3	3.0 (n=5)	0.001 M Fe(III) + 0.001 M H_2O_2 + 2 h ultrasonication duration [77]	4.9
Organosolv + Hydrothermal	57.2	159.6	194.1 (n=4)	Ethanol organosolv + Hydrothermal at 170–210 °C for 30 min [74]	376.3

MC: Microbial consortium; AAS: Aqueous ammonia soaking; NMMO: N-methylmorpholine-N-oxide; CA: Chemical antidote.

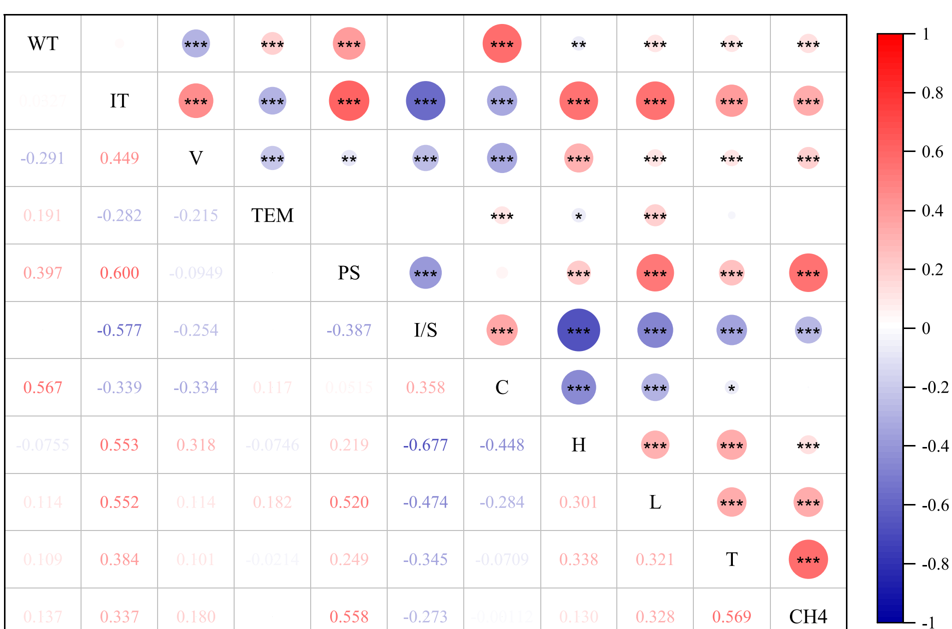

Fig. 5. Pearson correlation between pairwise variables. WT: Wood types; IT: Inoculum types; V: Volume (mL); Tem: Temperature (°C); PS: Particle size (mm); I/S: Ratio of inoculum to substrate (based on VS); C: Cellulose content (%); H: Hemicellulose content (%); L: Lignin content (%); T: Digestion time (d); CH4: Methane production (L/kg of VS). (*) $p < 0.05$; (**) $p < 0.01$; (***) $p < 0.001$.

= 0.9451, RMSE = 20.92) (Table 2 and Fig. 6a–c). This could be explained by the selection of major parameters affecting the methane yield from AD and by a greater number of data compared to the publications [37,82,83]. To visualize better the results, regression error characteristic (REC) curves were used to estimate the error in an absolute deviation form of all ML models (Fig. 6d). The REC curve represents the cumulative distribution function of the error, with a smaller area over the curve denoting greater accuracy. As shown in Fig. 6d, RF had the highest prediction accuracy among the three ML algorithms. RF is an ensemble learning method that constructs a multitude of decision trees and combines their outputs to improve the accuracy and stability of predictions [84,85]. Meanwhile, RF shows superior performance on high-dimensional, large, and noisy data, while avoiding overfitting problems [86]. Long et al. used six ML algorithms to predict methane yield by combining genomic data and their corresponding operational parameters and found that RF achieved the most accurate predictions when only operating parameters were used as input variables and when combining operating parameters with genomic data [38]. RF exhibited advantages of high generalizability and swift convergence when applied to AD data, which aligns with the results of this study. In general, the optimal RF model can reliably and precisely forecast and guide practical AD experiments.

To weigh the impact of various factors on methane production, RF was employed to assess feature importance and the results are illustrated in Fig. 7. The two most important factors were digestion time (40.5 %) and particle size (25.8 %). Firstly, the digestion time exhibits a close association with the methane production. Specifically, as time elapses, the availability of organic matter to microorganisms in an AD system increases, thereby leading to an escalation in cumulative methane production. Secondly, particle size plays an important role in AD by affecting the surface area of substrate. Dai et al. confirmed this view and illustrated that the reduction in particle size had a facilitative effect on methane production [87]. For lignocellulose composition, the lignin content of the substrate had a more significant effect on AD compared to cellulose and hemicellulose (Fig. 7). This was consistent with the established situation where lignin was the main obstacle to breakdown of lignocellulosic wastes [55]. It is worth noting that the temperature did not have an important effect, which could be explained by the data collected in this study mostly adopting similar temperatures (30–40 ℃). Therefore, thermophilic conditions could be future studies for the AD of wood waste. Overall, the outputs of the RF model could identify important factors influencing the AD system. Moreover, as the dataset is expanded and additional variables are incorporated, the outcomes have the potential to become even more representative.

3.5. Limitations and future perspectives

The production of cleaner energy based on AD as an alternative to fossil fuel has drawn increasing attention. Among the feedstocks for AD, lignocellulosic wastes and especially wood waste are less effective in methane production than other organic wastes [28]. Therefore, the data related to wood waste and AD are scarce and scattered in the literature. In this study, methane production data from wood waste under different AD systems was collected for *meta*-analysis, and the involved mutual variables were selected for ML, with the aim of providing a systematic insight into the potential for methane production from AD of wood waste. The *meta*-analysis showed that wood waste had a lower BMP than other organic wastes but had good pretreatment potential, while all three types of ML models accurately predicted methane production using the digestion parameters after a certain period of training. The existing limitations and future perspectives are summarized as follows.

The results of this study have several limitations due to the quality and quantity of data collected from publications. Firstly, very few studies have evaluated methane production from the AD of wood waste. In addition, most of these data were obtained from laboratory experiments, where feedstocks consisting of a single wood material were added to the AD in the experimental design. For example, the volume of AD system in several studies was as low as 60 mL [73], which is far less than the practical situation. The temperature collected in the dataset was only mesophilic, with thermophilic conditions often present in AD plants not fully represented. Therefore, some uncertainty exists when extrapolating the results of this study to practical AD of wood waste. Secondly, since the vast majority of studies were on a laboratory scale, the pretreatment techniques did not take into account the energy and material consumption and economics of practical applications. In contrast to chemical and physical pretreatment approaches, biological approaches can be more eco-friendly technique with low capital and operating costs [63]. Unfortunately, there is a lack of biological approaches, especially natural biodelignification systems, that are as rapid and effective as physical and chemical approach. Thirdly, for machine learning, the data distribution of some features was inconsistent owing to a variety of variations in experimental goals, methodologies, and conditions. Many publications cannot provide the data on the ten variables (wood types, inoculum types, volume (mL), temperature (℃), particle size (mm), ratio of inoculum to substrate (based on VS), cellulose content (%), hemicellulose content (%), lignin content (%), digestion time (d)) selected to form the ML dataset. In addition, the elemental composition of feedstock, generally missing in the publications, is also an important parameter for predicting methane production [37,83]. These situations limited the scale of the dataset available in this study.

The optimisation of AD is a complex issue that depends on multiple factors and cannot be directly and accurately measured [88]. To reduce the complexity of the experiments, a single wood type was commonly used. Therefore, due to the limited number of publications and data that can be extracted, it is difficult to systematically evaluate the effect of mixed wood types on AD and the performance of anaerobic co-digestion between wood waste and other organic wastes. In addition, current studies are focused on exploring the improvement of methane production from wood waste by different pretreatment technologies, while few studies have reported the impact of pretreatment on the microbiome. Among other lignocellulosic wastes, pretreatment techniques have been demonstrated to alter the microbial composition, especially functional microbes, that plays an important role in AD processes [61,89,90]. Therefore, future research should focus on the construction of a comprehensive database that includes studies with microbiome data under uniform experimental conditions and similar experimental methodologies.

4. Conclusions

To explore the BMP of wood waste, a *meta*-analysis based on 769 groups of datasets on methane production and wood waste was conducted. The results showed a 122 % lower BMP for wood waste compared to other organic wastes. However, this gap could be mitigated to 99 % when pretreatment techniques were considered, indicating that pretreatment techniques could be more effective for wood waste. Further analysis on different pretreatment techniques showed that the employment of pretreatment methods significantly improved the BMP of wood waste by 113 % and the combination of multiple pretreatment techniques was more effective than a single approach. Moreover, three ML algorithms were applied to predict methane production based on ten

Table 2
Performance of machine learning models on predicting methane production.

ML models	R^2	RMSE	MAE	STDEV
SVR	0.9451	20.9235	12.7287	86.6033
RF	0.9643	15.5247	6.9357	80.4058
ANN	0.9640	16.3031	9.9939	85.4359

SVR: support vector regression; RF: random forest; ANN: artificial neural network; RMSE: root mean square error; MAE: mean absolute error; STDEV: standard deviation.

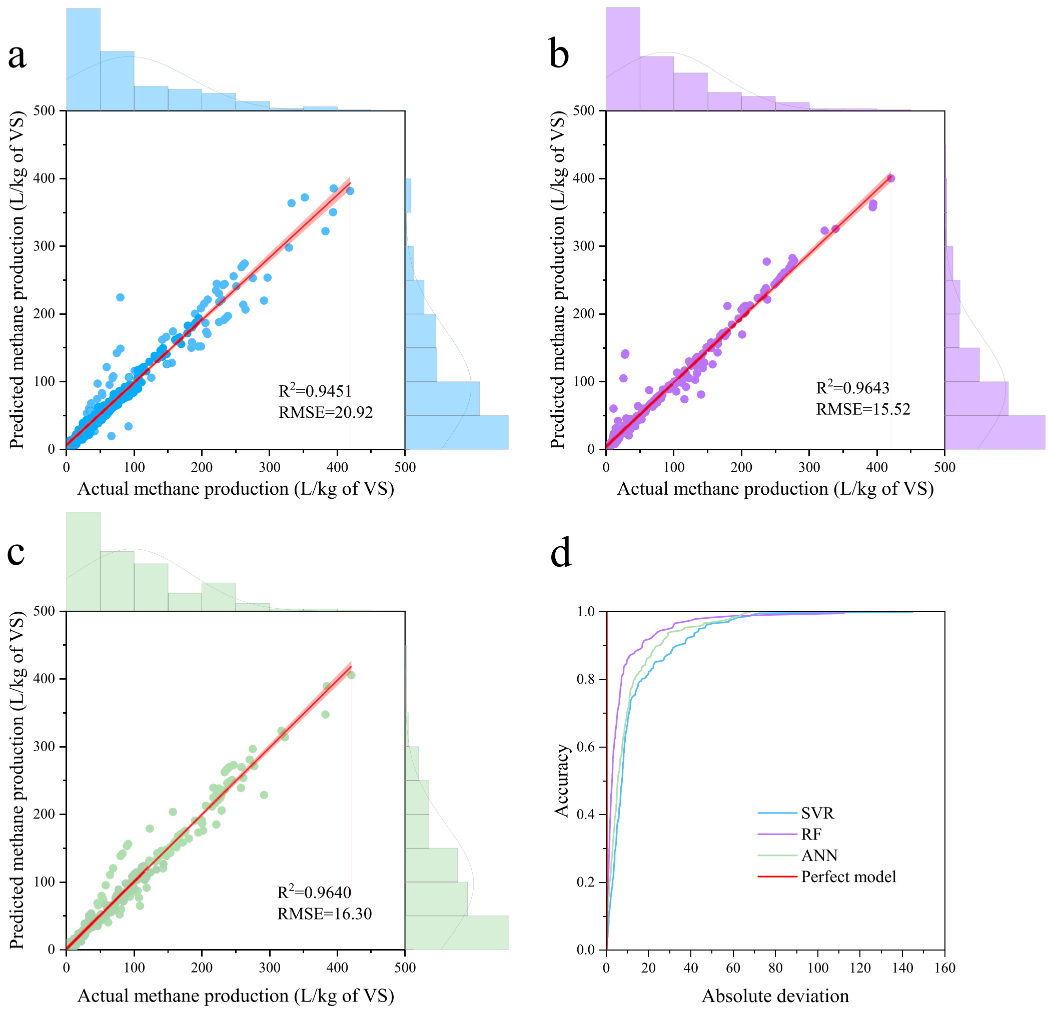

Fig. 6. Performance of the testing datasets of (a) support vector regression (SVR), (b) random forest (RF), and (c) artificial neural networks (ANN). (d) The regression error characteristic curves of three machine learning models.

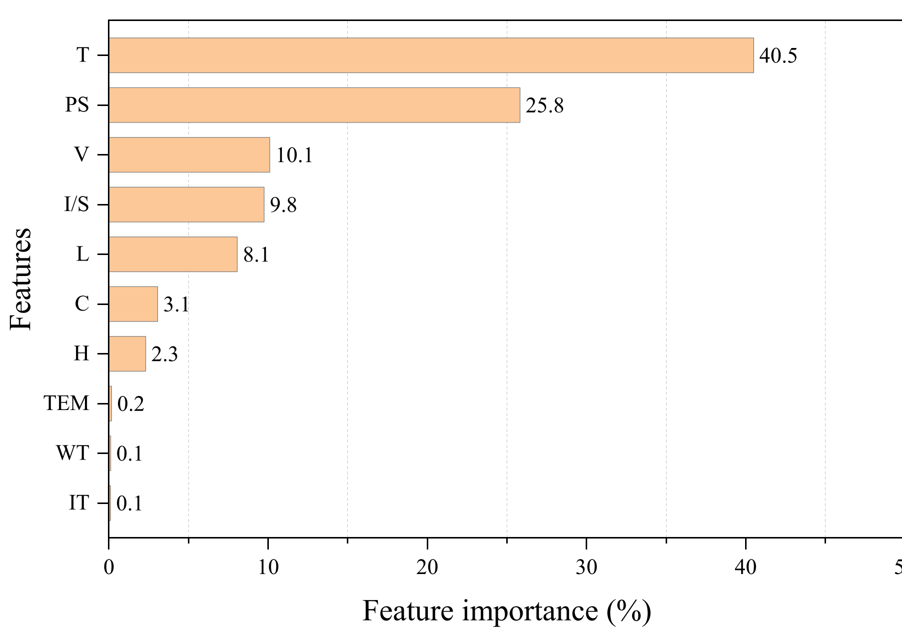

Fig. 7. Feature importance of each variable based on random forest. WT: Wood types; IT: Inoculum types; V: Volume (mL); Tem: Temperature (℃); PS: Particle size (mm); I/S: Ratio of inoculum to substrate (based on VS); C: Cellulose content (%); H: Hemicellulose content (%); L: Lignin content (%); T: Digestion time (d).

selected variables involved in the literature. Feature importance analysis revealed that digestion time and particle size presented the highest importance. The optimal algorithm was RF with the $R^2 = 0.9643$ and the RMSE value of 15.52 L/kg of VS in the testing dataset. Considering the size of the available data, more types of wood waste and AD parameters should be characterized to further explore the BMP of wood waste.

CRediT authorship contribution statement

Zhenghui Gao: Writing – original draft, Visualization, Methodology, Investigation, Data curation, Conceptualization. **Tianyi Cui:** Visualization, Methodology, Data curation. **Hang Qian:** Visualization, Methodology, Data curation. **Devin J. Sapsford:** Writing – review & editing. **Peter J. Cleall:** Writing – review & editing. **Michael J. Harbottle:** Writing – review & editing, Supervision.

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.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cej.2024.150496.

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