Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 7 Issue 8, August - 2020

Higher Heating Value Prediction Model From Proximate And Ultimate Analysis Data

Balogun Ayokunle O. Landmark University
Mechanical Engineering, Landmark University,
LMU, Omuaran, Nigeria
balogun.ayokunle@lmu.edu.ng

Lasode Olumuyiwa A. University of Ilorin.
Mechanical Engineering, University of Ilorin,
Unilorin, Ilorin, Nigeria
lasodeoa@gmail.com

McDonald Armando G. University of Idaho
Department of Forest, Rangeland, and Fire Sciences,
University of Idaho
armandm@uidaho.edu

***Abstract*—This study undertook the formulation of higher heating value (HHV) prediction model from 170 different biomass samples with about one-third being of African-origin. The data were collected from our previous studies and other open literature and subsequently subjected to a multivariable regression analysis technique. The model performance for this study was done in comparison to correlations obtained in the past with the aid of some statistical tools namely average absolute error (AAE) and average bias error (ABE). The models from this study with relatively higher accuracies are $0.2351 \cdot VM - 0.0775 \cdot ash$ and $0.3399 \cdot C + 0.3590 \cdot H$ respectively, for proximate and ultimate analyses. They both have AAE values less than 8%. It is noteworthy that the empirical relation for proximate analysis would be of profound utility within the African context giving the associated technical constraints in HHV determination.**

Keywords— Higher heating value; biomass; proximate; ultimate; multivariable regression

I. INTRODUCTION

In recent decades, there has arisen a grave global concern regarding the dwindling fossil fuel reserves, and the adverse environmental consequences, primarily, climate change and global warming phenomena, engendered by its utilization. In a bid to combat this challenge, biomass resource has been identified as an attractive renewable energy resource. It is the fourth most abundant primary energy source, after the conventional ones, namely, petroleum, coal, and natural gas [1]. Biomass materials are readily available at relatively cheaper prices – often as concomitant by-products of agro-industrial activities, constituting waste management and disposal challenges [2]. Another major merit is the fact that the utilization of biomass for thermal energy generation is carbon neutral as well as low in SOx and NOx emissions.

Typically, lignocellulosic biomass is used as a feedstock material for heating and electricity generation, biofuels production, and bioenergy applications. The design and simulation of efficient combustion and reaction systems require fundamental data of biomass physical and chemical characteristics alongside their calorific value. This value is the measure of heat energy liberated per unit mass of fuel during its complete combustion and it is expressed as either higher heating value (HHV) or lower heating value (LHV). The former accounts for the total enthalpy that includes the latent heat of vaporization of water, while the LHV excludes the latent heat. The calorific value determination can be undertaken experimentally with the aid of an adiabatic bomb calorimeter. However, this equipment and its operation could be expensive, time-consuming, and/or require some expertise, which in some instances may not be readily available [3], [4]. This necessitates the formulation of reliable empirical models that utilize data from relatively simple experiments. Hitherto, several HHV prediction correlations have been formulated based on characterization data from different organic materials, ranging from fossil fuels, mostly coal, to a vast array of biomass residues cutting across diverse regional locations [5]–[8].

One of the earliest model is the Dulong's linear relation for the estimation of coal's HHV; however, regarding biomass applications, it is severely limited [3]. Though there are more recent prediction models derived from biomass data, some of them are fraught with a number of imprecisions [7]–[9]. For instance, Vargas-moreno [3] opined that the inclusion of inter-related variables such as fixed carbon [FC] as an independent variable is mathematically questionable because it is usually estimated as a difference between 100% and the sum of the other elements (Volatile matter [VM], and ash [ash]) on a dry-basis. A similar argument could be made for the inclusion of elemental oxygen [O] from elemental analysis for the development of HHV prediction models. Furthermore, some authors fail to state categorically the basis on which their data is being reported [3]. In terms of regional spread, most of the regression models have been developed from biomass data obtained in Europe and Asia with little focus on biomass resources emanating from [1], [10]. Garcia et al [7] worked on biomass of Spanish origin and through multivariable regression analysis (MVRA) proposed four correlation equations. Similarly, Thipkhunthod et al [6] and Chang et al [11] respectively derived regression models from Thailand-based and Taiwan-based biomass materials. Even in instances of a wider geographical reach, information on biomass originating from Africa are virtually absent. This is clearly demonstrated in a recent publication [1]. According to Azeez et [12], variation in the elemental constituent of an African hardwood species relative to a counterpart European species, significantly influenced the outcome of a pretreatment process. The dependence of biomass characteristics on geographical location, climatic condition and management practices has also been underscored in literature [13]. To the best of the authors' knowledge, this is a first attempt to include a sizeable amount (more than 30%) of characterization data gathered from biomass of African origin.

The aim of this research was to formulate an HHV prediction models from proximate and ultimate analysis data using an MVRA technique. The study also compared the predictive accuracy of the model from this study with selected ones.

II. MATERIALS AND METHODS

A. *Data Collection*

A database of proximate, ultimate analyses and HHV on 170 biomass samples was obtained from our previous study [14] and other published literature as presented in Table 1. Specifically, the data gathering was restricted to articles published not later than 2010 and they were reported on a dry-basis and dry-ash-free basis [13]. The data were also from those in which the countries of origin of the sample source were explicitly stated and experimental HHV measurements taken. To ensure consistency in terms of the basis of experimental reporting, those reported otherwise, were converted into dry-basis (db) and dry-ash-free (daf) basis for proximate and ultimate analysis data respectively. The data on chlorine, where present, were ignored. Furthermore, a subset of 136 samples was selected randomly for the model development, while the remaining data sets were incorporated for model validation.

The samples under consideration cover a vast variety of lignocellulosic biomass that may be broadly grouped into four categories namely (i) herbaceous and agricultural residues (HAR), (ii) herbaceous and agricultural grasses (HAG), (iii) herbaceous and agricultural straws (HAS), and (iv) wood and woody biomasses (WWB) (Vassilev et al. 2010). Table 1 shows that volatile matter (VM) and ash contents respectively varied from 59.2 to 95.5% and 0.1 to 27%, while C, H, N, and S contents varied from 24.51 to 59.23%, 0.27 to 11.28%, 0.07 to 8.03%, and 0 to 3.19%. The HHV ranged from 12.83 to 27.63 MJ/kg.

Table 1 Proximate, ultimate analyses and HHV data from published literature

Biomass residues	Proximate Analysis			Ultimate Analysis					HHV_{exp} (MJ/kg)	Country of Origin	Ref
	VM (wt%)	Ash (wt%)	FC^a (wt%)	C (%)	H (%)	N (%)	S (%)	O^a (%)			
Herbaceous and Agricultural Residues (HAR)											
Palm stem	81.2	3.5	15.3	49.23	6.11	0.29	0.13	44.05	17.38	Tanzania	[15]
Palm branch	79.6	7.8	12.6	49.47	6.08	0.21	0.17	42.63	16.24		
Palm fiber	79.0	11.8	9.3	59.23	8.06	0.79	0.08	31.77	21.98		
Coffee husks	83.2	2.5	14.3	50.61	6.25	0.83	0.07	42.21	18.34		
Masai Cashew nuts	84.1	1.9	14	57.07	7.03	0.45	0.05	35.36	22.38		
Olam Cashew nuts	84.8	2	13.1	58.05	7.14	0.46	0.04	34.28	22.83		
Rice husks*	59.2	26.2	14.6	48.25	6.1	0.26	0.03	45.26	13.24		
Rice bran*	64.6	21.1	14.2	47.91	6.34	0.7	0.06	44.87	13.93		
Sugarcane bagasse	80.5	3.3	16.2	49.77	6.11	0.16	0.02	43.87	17.33		
Sisal leaf	80.2	7.2	12.6	50.64	6.14	0.15	0.03	42.99	17.23		
Sisal bole	84.1	3.1	12.8	49.54	6.19	0.1	0.03	44.07	17.2		
Sisal pole	79.3	6.1	14.6	50.03	6.39	1.77	0.14	41.62	17.35		
Cocoa pod	76.3	12	11.6	43.87	5.82	2.23	0.57	47.28	17.08	Nigeria	[16]
Cocoa pod	66.08	14.9	19	50.28	6.69	0.19	0.19	42.64	18.1	Colombia	[17]
Corncob	88.4	3.2	8.3	43.3	6	0.93	-	49.37	16.99	Ghana	[16]
Rice husks*	63.7	27	9.3	34.9	5.15	0.31	0.64	59	14.08	Ghana	
Sugarcane bagasse	86.8	4.3	8.9	44.31	5.73	0.63	-	49.11	16.88	Ghana	
Jatropha cakes	80.6	7.2	12.2	44.42	6.23	4.33	0.51	44.51	21.24	Nigeria	
Parinari fruit shell	80.3	4.8	14.9	48.04	5.76	2.13	0.1	43.53	20.47	Nigeria	
Corncob	80.2	3.1	16.7	49	6	0.3	0.08	44.7	17.2	South Africa	[18]
Sugarcane bagasse	76.9	5.3	17.8	50.3	6.3	0.3	0.07	43.1	17.5	South Africa	
Moringa peregrina seed husk	78.9	2.5	18.6	45.42	6.34	0.94	0.57	46.73	18.21	Sudan	[19]
Jatropha seed husk	64.9	3.9	31.1	50.9	5.8	0.8	0.08	39.5	17.98	India	[20]
Moringa peregrina seed oil cake	80.3	4.1	15.6	46.42	7.76	8.03	3.19	36.6	20.65	Sudan	[19]
Sweet sorghum bagasse	79.2	4.6	16.2	43.5	5.6	0.28	0.13	50.5	17.3	South Africa	[21]
Almond shell	82	2.2	15.8	46.35	5.67	0.3	0.22	47.2	18.28	Spain	[22]
Olive stone	78.3	1.4	20.35	46.55	6.33	1.81	0.11	45.2	17.88		
Pine kernel shell	77.6	2.7	19.7	47.91	4.9	0.31	0.6	46.28	18.89		
Chestnut shell	67	3.9	29	42.31	5.17	0.42	0.33	51.77	14.31		
Areca nut husk	80.6	2.5	16.9	48.8	5.79	1.95	0.1	43.45	18.21		
Coconut shell	79.2	1.4	19.4	47.93	6.05	0.15	0.24	45.63	18.88		
Coffee husks	76.2	5.8	18	45.06	6.42	2.53	0.48	45.51	18.33		
Corncob	83	2.4	14.6	44.78	6.02	0.22	0.21	48.77	17.69		
Hazelnut shell	77	2.2	20.8	47.8	6.14	0.27	0.16	45.64	18.87		
Pea husk	83	4.5	12.5	24.51	0.27	0.42	1	73.8	15.46		
Peanut shell	81	2.5	16.5	49.35	6.4	1.05	0.24	42.96	20.01		
Pistachio shell	82.5	1.3	16.2	44.69	5.16	0.11	0.18	49.87	16.2		
Rice husks*	73	13.7	13.3	26.69	2.88	0.21	0.17	70.05	15.9		
Walnut shell	79	2.3	18.7	46.97	6.27	0.22	0.1	46.44	18.38		
Banana peel	73	4.5	22.5	50.4	6.3	2.56	0.39	40.4	18.87	China	[23]
Durian shell	73.9	3.3	22.8	40.98	4.44	1.31	0.34	52.93	13.79	Malaysia	[24]
Coffee tree leaves	74.71	7.17	18.12	53.97	6.55	3.54	0.43	35.5	19.45	Brazil	[25]
Coffee parchment	74.07	5.84	20.09	50.69	6.23	0.82	0.2	42.05	18.3	Brazil	
Sugarcane bagasse	81.86	2.04	15.98	42.09	5.42	0.18	0.12	51.5	16.79	Colombia	[26]
Corn stover	82.13	5.01	12.86	56.08	5.97	0.65	0.11	37.19	18.78	USA	[27]
Beer bagasse	79	3	18	50.13	7.16	3.58	0.25	38.88	21	Spain	[28]
Orange Juice residues	76	6	18	46.78	6.38	1.06	0.05	45.72	17	Spain	
Adzuki bean waste	76.1	6.24	17.66	39.41	10.68	2.95	0.93	46.03	19.85	Malaysia	[29]
Oil palm empty fruit bunch	81.53	6.28	12.19	45.23	6	1.21	0.13	47.43	17.57	Malaysia	[30]
Oil palm trunk	77.1	18.6	4.29	50.1	7.59	1.04	0.11	41.2	14.5	Malaysia	[31]
Seed cake (jatropha)	68.63	5.28	26.08	46.15	6.47	4.48	0.2	42.71	19.28	Botswana	[32]
Jatropha stem	70.68	7.94	21.39	43.68	6.32	1.33	0.21	48.46	18.39	Botswana	
Jatropha fruit husk	61.51	19.74	18.75	36.05	5.37	1.07	0.37	57.15	13.57	Botswana	
Empty fruit bunch	86.93	3.63	9.44	46.62	6.45	1.21	0.035	45.66	17.02	Malaysia	[33]
Empty fruit bunches	77.99	4.98	17.04	40.93	5.42	1.56	0.31	51.78	16.8	Malaysia	[34]
Palm kernel shell	69.2	10.5	16	41.33	4.57	0.99	0.09	53.02	16.3	Malaysia	
Palm mesocarp fiber	73.04	10.83	16.14	43.19	5.24	1.59	0.19	49.79	19	Malaysia	
Palm kernel shell	77.5	2.2	20.3	56.1	5.9	0.4	0.03	37.6	16.3	Malaysia	[35]
Bambara Groundnut	73.83	10.1	16.08	34.63	11.28	1.16	1	51.93	19.19	Malaysia	[29]

Tobacco waste	62.44	20.78	16.78	46.96	5.92	3.55	0.66	42.91	13.88	China	[36]
Mallee residue	77.9	2.9	19.2	52.71	6.01	0.53	0.08	40.67	20.42	Australia	[37]
Soybean waste	74.8	5	20.2	43.8	6.3	1.4	0.8	48.5	18.77	India	[38]
Almond shell	75.08	4.09	20.83	49.38	5.82	0.56	0.25	44	18.71	USA	[39]
Almond hull	71.24	8.57	20.19	49.4	6.02	1.08	0.22	43.28	17.66	USA	
Corn cob	79.31	7.23	13.46	41.16	5.11	0.46	-	53.27	16.73	South Africa	[40]
Pine cone	78.62	1.54	19.85	56.47	6.55	0.37	-	36.61	17.45	Turkey	[41]
Corn stalk	73.3	11.7	15	50.61	6.31	0.67	-	42.41	12.83	Turkey	
Peanut shell	73.9	2.3	23.8	52.73	6.1	1.33	-	39.84	16.35	Turkey	
Potato peel	76.5	9.3	14.2	43.8	6	4.1	-	46.2	17.4	USA	[42]
Indigofera biomass residue	87.7	10.2	2.1	49.2	7.2	2.5	-	41.1	17.09	India	[43]
Soy peel	91.4	1.17	7.44	45.04	6.7	2.9	-	45.35	17.9	Brazil	[44]
Rice husks	71.24	12.5	16.27	35.86	4.4	0.28	-	59.46	16.35	Brazil	
Coffee husks	75.4	2	22.7	43.34	5.55	2.25	-	48.86	18.06	Brazil	
Coconut fibers	77	2.96	20.05	47.4	5.41	0.55	-	46.64	18.7	Brazil	
Bamboo	81.08	1.71	17.2	44.6	5.55	0.91	-	48.93	18.33	Brazil	
Banana stalk	70.86	7.76	21.41	37.95	4.73	1.46	-	55.85	15.73	Brazil	
Banana stem	81.71	8.14	10.14	39	5.44	0.82	-	54.84	16.13	Brazil	
Mbwazirume peel	78.29	6.52	15.19	46.94	5.79	0.23	0.3	46.74	18.28	Uganda	[45]
Nakyinyika peel	79.86	5.44	14.7	46.22	5.6	0.41	0.36	47.41	17.76	Uganda	
Palm kernel shell	76.1	2.9	21	55.2	6.4	0.45	-	37.95	21	Nigeria	[46]
Rice husk	68.25	14.83	16.92	39.48	5.71	0.67	-	54.12	17.34	Brunei	[47]
Oil palm frond	82.12	11.9	5.98	37.52	6.9	3.52	0.28	51.77	14.49	Malaysia	[48]
Oil palm trunk	85.7	8.11	6.19	38.26	8.21	0.59	0.44	52.5	16.34	Malaysia	[48]
Empty fruit bunch	88.71	6.98	4.32	38.26	8.21	0.59	0.44	52.5	16.07	Malaysia	[48]
Palm kernel shell	71.84	11	17.16	48.36	7.66	1.03	0.38	42.57	17.32	Malaysia	[48]
Rice husk	69.67	19.68	10.63	37.43	8.01	0.82	0.37	53.37	14.37	Malaysia	[48]
Kenaf	86.63	6	7.36	40.71	9.38	0.32	0.47	49.12	16.66	Malaysia	[48]
Sorghum bicolour glume	78.9	7.54	13.6	42.4	5.27	0.74	-	51.6	16.4	Nigeria	[49]
Tea waste	72.92	5.75	21.33	48.6	5.43	2.6	-	43.37	27.63	India	[50]
Herbaceous and Agricultural Straw (HAS)											
Rice straw	81.13	12.77	6.09	39.89	9.36	0.38	0.59	49.81	16.15	Malaysia	[48]
Barley straw	84.3	10.5	5.2	41.4	6.2	0.63	0.01	51.7	15.7	Canada	[51]
Flax straw	87.2	3.3	9.6	43.1	6.2	0.68	0.09	49.9	17	Canada	
Corn straw	82.6	8.1	12.9	42.65	5.57	1.49	-	49.16	16.24	Ghana	[16]
Barley straw	77.9	6.1	16	40.69	6.95	1.64	0.23	50.5	17.37	Spain	[22]
Rye straw	79.9	3.2	16.9	40.18	6.85	1.16	0.32	51.48	17.11	Spain	
Wheat straw	76	5.3	18.19	45.58	6.04	1.18	0.59	46.6	17.34	Spain	
Wheat straw	68.23	17.04	14.72	45.69	6.84	1.4	0.25	45.81	14.86	Mexico	[52]
Wheat straw	73.9	4.6	21.1	46.2	6.3	0.41	0.01	47.11	15.6	Canada	[53]
Wheat straw	74.8	8.64	16.5	40.6	6	0.19	0.9	53.2	17.62	India	[38]
Herbaceous and Agricultural Grass (HAG)											
Timothy grass	82	1.2	16.8	42.4	6	1.03	0.15	50.4	16.7	Canada	[51]
Miscanthus	79	9.6	11.4	47.09	6.3	0.1	0.1	46.42	18.07	Spain	[22]
Timothy grass	76.1	4.4	19.5	49.3	7.1	1.5	0.1	42	18.6	Canada	[54]
Switch grass	82.58	2.86	14.56	50.25	6.51	0.36	0.08	42.8	18.87	USA	[27]
Timothy grass	82.8	3.1	13.3	45.1	6.3	1.3	0.1	47.1	15.9	Canada	[53]
Napier grass	81.51	1.75	16.74	49.48	6.12	1.01	0.33	43.07	18.11	Malaysia	[55]
Grass	76.5	13	10.81	42	5.21	2.03	-	50.95	16.77	Brazil	[44]
Green banagrass	76.6	6.9	16.5	48.2	5.56	0.36	0.07	45.81	17.8	USA	[56]
Purple banagrass	74.5	7.9	17.6	47.5	5.53	0.43	0.06	46.48	17.6	USA	
Guinea grass	73.5	8.2	18.4	47.3	5.42	0.33	0.06	46.89	17.4	USA	
Imperata cylindrica	77.27	3.19	19.54	44.38	5.65	0.82	0.09	49.06	18.39	Brunei	[57]
Imperata cylindrica	82.79	0.9	16.31	43.19	5.92	0.59	0.14	50.17	17.03	Nigeria	[58]
Elephant grass	72.54	8.26	19.2	39.63	6.31	1.7	0.2	52.16	15.77	Brazil	[59]
Wood and Woody Biomass (WWB)											
Pinewood	87.5	1.6	10.3	49	6.4	0.14	0.01	44.4	19.6	Canada	[51]
Cytisus multiflorus (Shoot)	82.48	1.32	16.2	46.8	6.97	1.26	-	44.93	22.25	Portugal	[60]
Erica australis (shoot)	80.72	1.38	17.9	50.54	7.14	0.64	-	41.64	24.12	Portugal	
Pterospartum tridentatum (shoot)	81.1	1.44	17.45	48.64	7.07	0.68	-	43.57	21.37	Portugal	
Ulex europaeus (shoot)	84.46	1.47	14.06	47.01	6.95	0.96	-	45.03	21.87	Portugal	
Cytisus multiflorus (Shoot)	80.81	1.37	17.83	48.51	6.51	2.04	-	42.91	22.26	Spain	
Erica australis (shoot)	79.65	1.38	18.97	49.23	6.22	0.84	-	43.67	24.4	Spain	

Pterospartum tridentatum (shoot)	80.32	1.21	18.47	49.41	6.74	0.97	-	42.84	22.14	Spain	
Ulex europaeus (shoot)	80.8	1.56	17.64	49.11	6.52	1.73	-	42.6	21.24	Spain	
Mango stem	83.5	4.5	12	50.28	6.08	0.14	0.01	43.47	16.9	Tanzania	[15]
Softwood	85.3	0.41	14.27	47.7	5.7	0.96	0.16	45.5	18	South Africa	[21]
Hardwood	84.7	0.48	14.82	46.4	5.5	0.1	0.01	48	18	South Africa	
Pine chips	81.6	0.6	17.8	48.15	5.59	0.09	0.28	45.9	19.43	Spain	[22]
Pine shaving	85	0.8	14.2	48.67	5.08	0.07	0.26	45.92	19.79	Spain	
Chestnut tree shaving	79	0.4	20.6	45.88	5	0.12	0.27	48.73	17.62	Spain	
Pine sawdust	84.58	2.24	13.18	50.3	6	0.69	-	42.99	18.44	India	[61]
Sal sawdust	83.31	1.25	15.44	49.83	6.01	0.58	-	43.56	18.2	India	
Coffee (Primary branch)	80.62	2.42	16.95	50.31	6.13	0.92	0.36	42.28	19.2	Brazil	[25]
Coffee stem	83.7	1.67	14.62	50.64	6.12	1.86	0.21	41.16	19	Brazil	
Pine wood	76.9	2.5	20.6	50	6.3	0.1	0.1	43.5	18.1	Canada	[53]
Ceiba pentandra	82.43	4.72	12.85	55.26	5.3	0.48	0.05	38.91	20.33	Ghana	[62]
Triplochiton scleroxylon	80.97	2.01	17.02	56.83	4.08	0.56	0.09	38.44	21.6	Ghana	
Aningeria robusta	75.23	5.04	19.73	55.08	3.83	0.48	0.21	40.4	20.89	Ghana	
Terminalia superba	79.64	2.96	17.4	56.29	3.88	0.62	0.06	39.15	22.22	Ghana	
Piptadenia africana	80.6	0.61	18.79	57.65	4.2	0.71	0.05	37.39	22.17	Ghana	
Celtis mildbreadii	83.7	3.71	12.59	55.85	4.21	0.69	0.06	39.19	20.16	Ghana	
Grape stem	73	6	22	52.04	6.37	1.06	0.16	40.36	19	Spain	[28]
Pine	84.46	0.36	15.18	50.8	6.06	0.3	0.01	42.82	19.91	Spain	[63]
Black Poplar	82.31	1.1	16.59	50.4	5.96	0.39	0.02	43.23	19.63	Spain	
Chestnut	82.28	0.31	17.41	49.81	5.66	0.26	0.01	44.26	19.08	Spain	
Almond tree	75.03	4.56	20.41	50.91	5.84	0.94	0.23	42.08	19.39	USA	[39]
Pine wood	81.4	2.6	16	43.28	5.1	0.35	-	51.27	17.94	South Africa	[40]
Hybrid poplar	89.4	0.8	9.8	46.7	6.1	0.4	-	46.8	19.6	USA	[42]
Pine chips	85.98	0.27	13.76	47.21	6.64	0.17	-	45.76	18.46	USA	[64]
Logging residue (Pine)	82.17	1.77	16.07	47.29	6.2	0.42	-	45.19	18.79	USA	
Yemane tree sawdust	74.47	6.68	18.85	45.42	5.91	0.51	-	48.16	16.29	India	[65]
Sawdust	83.88	0.11	16	50.3	6.08	0.15	-	43.43	20	Brazil	[44]
E. grandis	88.4	0.1	11.5	48.45	7.52	0.11	0.06	43.86	19.2	Uganda	[66]
T. glaucescens	83.9	1	15.1	48.24	7.91	0.24	0.05	43.56	19.3	Uganda	
A.hockii	83.8	1.1	15.1	48	7.2	0.23	0.05	44.52	19.2	Uganda	
C.molle	82.6	2.1	15.3	47.9	7.69	0.27	0.05	44.09	19.1	Uganda	
Gmelina	80.9	1	18.1	51.9	6.3	0.16	-	41.64	20.8	Nigeria	[46]
Terminalia	80.2	2.2	17.4	50.1	5.9	0.33	-	43.67	19.4	Nigeria	
Lophira	78.1	1.6	20.3	52.7	6.6	0.28	-	40.42	21.1	Nigeria	
Nauclea	80.6	0.7	18.8	53.5	6.3	0.64	-	39.56	22.9	Nigeria	
Wood	77.92	0.27	21.81	49.06	6.31	2.08	0	42.55	18.78	UK	[67]
A. pedicellaris	92.7	1.68	5.61	51.7	5.85	0.54	-	42	20.1	Nigeria	[49]
T. grandis	95.5	0.7	3.8	49.6	6.3	0.4	-	43.7	19.8	Nigeria	
T. ivorensis	82.3	0.32	17.4	48.6	6	0.44	-	45	17.3	Nigeria	
Wood bark (*Calophyllum inophyllum*)	76.9	2.43	20.66	45.68	7.65	2.14	0.66	43.87	21.14	India	[68]
Coffee stem bark	75.63	4.33	20.03	54.41	6.59	2.13	0.21	36.66	19.2	Brazil	[25]
Palm shells	75.4	4.6	20	54.02	5.98	0.38	0.03	39.54	19.29	Tanzania	[15]
Cocoa beans husk	69	9.96	21.04	43.25	5.89	2.64	0.29	47.93	17.31	Spain	[22]
Sorghum bicolour stalk	82.9	3.25	13.8	46.2	5.85	0.44	-	47.6	17.9	Nigeria	[49]
Wheat straw	83.3	1.4	15.3	41.6	6.1	0.14	0.06	52.1	20.3	Canada	[51]
Wheat straw	76.3	5.2	18.5	48.53	6.25	1.5	0.16	43.57	19.96	Australia	[37]
Switch grass	84.2	3.9	11.9	43.8	6.4	0.4	0.1	49.4	19.8	United States	[69]
Coffee (Secondary branch)	75.31	3.45	21.23	51.82	6.4	1.51	0.21	40.06	19.2	Brazil	[25]

[a] calculated by difference

B. *Statistical Analysis and Multivariable Regression Modelling*

Regression analysis helps to build a probabilistic model that shows the correlation between a response variable and a single predictor (simple regression) or more than one predictor variables (multiple regression). The MVRA is a robust technique that takes into account the mutual effects of the explanatory variables on the output variable. The model that relates n independent variables, X_i , $(1 \leq i \leq n)$, and m dependent variables Y_j, $(1 \leq j \leq m)$ is expressed as (1),

$$Y_j = \sum_{i=1}^{n} \alpha_n \; X_n + \beta_j \qquad (1)$$

where $\alpha_i, (1 \leq i \leq n)$ is a regression coefficient that depicts the dependence of Y_j when X_i changes by one unit, while β_j is a constant termed correction factor and j is the number of observation. Table 2 presents twelve established and relatively recent HHV models in published literature. For instance, equations. (2) – (11) were formulated in the 1920s for biomass, while equation (12), though for biomass, and equation (13), for coal, are several decades old. These correlation models were selected for the purpose of comparison of the predictive capabilities of the proposed HHV models in this study. To develop a functional relation in terms of the characteristic properties of biomass, the influence of the predictor variables (VM, ash, C, H, N, and S) on the estimation of HHV was initially investigated with the MATLAB *corrcoef* command. This yielded the matrix of Pearson's R, and the *p*-values with a non-correlation hypothesis test at a significance level of 5%. Thereafter, a regression analysis was conducted by plugging the data into a spreadsheet and observing the lines of best fits based on ANOVA results. It is noteworthy that primary consideration was given to the statistically significant variables. However, there was an exemption of FC and O variables in the statistical analysis as well as the regression modelling because their measurements were not independently taken. Two statistical parameters (Eqs. 14 and 15), which included, the average absolute error (AAE), and average bias error (ABE) were deployed to study the model performance.

$$AAE = \frac{1}{m} \sum_{j=1}^{m} \left| \frac{HHV_{pre,j} - \overline{HHV}_{exp}}{HHV_{exp,j}} \right| \times 100\% \qquad \text{Eq.14}$$

$$ABE = \frac{1}{m} \sum_{j=1}^{m} \left(\frac{HHV_{pre,j} - \overline{HHV}_{exp}}{HHV_{exp,j}} \right) \times 100\% \qquad \text{Eq.15}$$

Where the *HHV_{pre}* and *HHV_{exp}* are predicted and the experimental HHV respectively, the bar indicates an average value, *j* is the *j*th number of *m* experimental data. The AAE indicates the discrepancy between the predicted and the experimental values. By implication, a lower AAE signifies a higher accuracy for a given model. On the other hand, a positive ABE value implies an overestimation, while a negative value indicates an underestimation.

Table 2 Selected HHV models for biomass samples from published literature.

Model No	**HHV Equations**	**Based on**	**Unit**	**REF**
Eq.2	$HHV = 10.982 + 0.1136 \cdot VM - 0.2848 \cdot ash$	P	MJ/kg	[9]
Eq.3	$HHV = -17.507 + 0.3985 \cdot VM + 0.2875 \cdot FC$	P	MJ/kg	[9]
Eq.4	$HHV = 1.83 \times 10^4 - 3.98 \cdot ash^2 - 112.10 \cdot ash$	P	kJ/kg	[7]
Eq.5	$HHV = 0.3536 \cdot FC + 0.1559 \cdot VM - 0.0078 \cdot ash$	P	MJ/kg	[70]
Eq.6	$HHV = 0.1905 \cdot VM + 0.2521 \cdot FC$	P	MJ/kg	[10]
Eq.7	$HHV = 0.2949 \cdot C + 0.8250 \cdot H$	U	MJ/kg	[10]
Eq.8	$HHV = 338.4 \cdot C + 244.2$	U	kJ/kg	[8]
Eq.9	$HHV = 1.87 \cdot C^2 - 144 \cdot C - 2820 \cdot H + 68.3 \cdot C \cdot H + 129 \cdot N + 20147$	U	kJ/kg	[71]
Eq.10	$HHV = 5.22 \cdot C^2 - 319 \cdot C - 1647 \cdot H + 38.6 \cdot C \cdot H + 133 \cdot N + 21028$	U	kJ/kg	[71]
Eq.11	$HHV = 0.3491 \cdot C + 1.1783 \cdot H - 0.1005 \cdot S - 0.1034 \cdot O - 0.015 \cdot N - 0.0211 \cdot ash$	U	MJ/kg	[72]
Eq.12	$HHV = 0.4373 \cdot C - 1.6701$	U	MJ/kg	[73]
Eq.13	$HHV = 0.336 \cdot C + 1.418 \cdot H - (0.153 - 0.00072 \cdot O) \cdot O + 0.0941 \cdot S$	U	MJ/kg	[5]

P – proximate; U – ultimate

III. RESULTS AND DISCUSSION

A. Statistical Analysis and Multivariable Regression Modelling

The R and p statistics represent the correlation coefficients, and the probability of obtaining a correlation by chance respectively. Table 3 presents the aforementioned statistic parameters for the selected variables in relation to HHV estimation.

Table 3 R and *p* values for HHV related to proximate and ultimate analyses

	VM	Ash	C	H	N	S
R values	0.3206	-0.5520	0.5162	0.1135	0.08826	-0.0646
P values	0.0000	0.0000	0.0000	0.1405	0.2524	0.4027

The statistically significant correlation is demonstrated by VM, Ash and C contents as indicated by the *p*-values < 0.05. The strongest relationship exists for the ash content, albeit, with a negative effect, while in sequence, a positive correlation exist for C and H. However, the influence of the other variables is statistically negligible.

Table 4 Developed HHV models and their regression statistics

Model No	Equation	R^2	Adjusted R^2	Standard Error	Significance F	*p*-value[b]	Analysis Type
Eq.14	$0.2351 \cdot VM - 0.0775 \cdot ash$	0.985	0.977	2.257	4.306×10^{-122}	<0.05	Proximate
Eq.15	$0.3399 \cdot C + 0.3590 \cdot H$	0.986	0.979	2.149	6.098×10^{-125}	<0.05	Ultimate
Eq.16	$0.3787 \cdot C + 2.3245 \cdot S$	0.987	0.979	2.130	2.310×10^{-125}		
Eq.17	$0.3769 \cdot C + 0.462 \cdot N$	0.986	0.979	2.154	8.802×10^{-125}		

[b] both variables

Table 4 presents the empirical models developed through the MVRA technique based on proximate and ultimate analysis data in this study. Following the non-correlation hypothesis test, variables were considered in succession utilizing a stepwise regression technique. It is shown that the estimations of the lines of “best-fit” for the models are high with the least, R^2 = 0.985, being the model proposed from proximate analysis data. It is important to note that C variable features prominently in the functional relations. This attests to the fact that it contributes significantly to the energy content of biomass resources [10], [74]. The proposed models, equations 14-17, are relatively simple linear relations free of some common mathematical blunders noted earlier, that is, the inclusion of FC and O variables [1], [7], [71] .

Sequel to the incorporation of the validation data, HHVs were approximated using equation 2-17 and model performance was undertaken. Figure 1 shows the values of AAE and ABE parameters for the empirical relations developed in this study and those from other published literature. Unlike some previous correlations (equations 8, 12, 13), all the developed models have the capability to estimate biomass HHV’s with an AAE less than 10%, suggesting a relatively higher accuracy. In addition, it may be inferred that the accuracy of a model is not necessarily dependent on the inclusion of large number of predictor variables as aptly illustrated by equations 11 and 13. Contrary to the report by Yin et al [10], the values of AAE for some of the correlations derived from proximate data compares favorably well with those of ultimate data. In fact, equations 14 and 15 respectively are 7.21 and 7.87%. It is noteworthy that both models have absolute values of ABE less than 2.0%. In real terms, however, they are both negative values implying a tendency for low underestimation. This is significant because of its practical utility in less developed countries of Africa, where accessibility to sophisticated analytical instruments and the requisite expertise could be a challenge. Therefore, equation 14 particularly, provides a handy and a simple tool for HHV estimation from the results of much less complicated experiments such as proximate analysis. The empirical models developed from ultimate analysis data have the least absolute value of ABE (1.19 to 1.49) relative to previously published models (1.83 to 12.61); implying a minimal bias error in their predictive capabilities. Additionally, equation 15 presents the lowest AAE with a minimal underestimation of 1.37% among the models in the ultimate analysis. This attests to its high predicative capability.

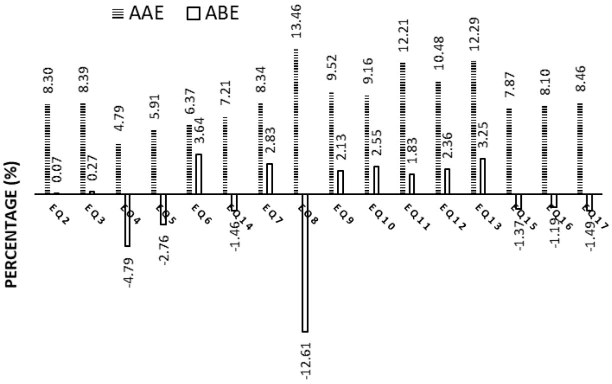

Figure 1 Plot of AAE and ABE of the 16 HHV models.

Figures 2a and 2b respectively compare the predicted and measured HHV based on Eqs. 14 and 15 for all biomass materials under investigation. It is demonstrated that Figure 2b has far less number of outliers that is an indication that Eq. 15 provides a relatively more accurate correlation. This is in agreement with a previous report [10].

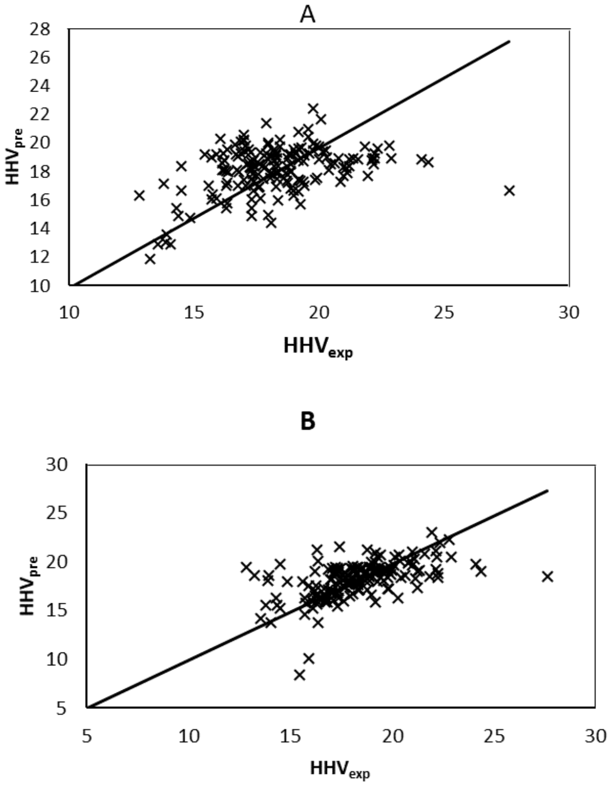

Figure 2 Plot of predicted and experimental HHV for the proposed model based on (A) proximate analysis – equation14 and (B) ultimate analysis **–** equation 15

Conclusion

This research sought to develop an HHV prediction model for biomass of diverse origin through the use of a MVRA technique. The correlations obtained from this study demonstrated relatively higher level of accuracy and lower tendency for overestimation. The prediction model from proximate analysis is highly recommended because of its simplicity and suitability within the African context in the determination of energy values of biomass materials.

Acknowledgment *(Heading 5)*

None to acknowledge

References

[1] I. Boumanchar, K. Charafeddine, Y. Chhiti, F. Ezzahrae, and M. Alaoui, “Biomass higher heating value prediction from ultimate analysis using multiple regression and genetic programming,” *Biomass Convers. Biorefinery*, 2019, doi: 10.1007/s13399-019-00386-5.

[2] O. A. Lasode and A. O. Balogun, “Wood wastes generation in Ilorin Metropolis: Problems, Management and Prospects,” in *25th INternational Conference on Solid Waste Technology and Management*, 2010, pp. 586–592, doi: 10.5555/asdfas.

[3] J. M. Vargas-moreno, A. J. Callejón-ferre, J. Pérez-alonso, and B. Velázquez-martí, “A review of the mathematical models for predicting the heating value of biomass materials,” *Renew. Sustain. Energy Rev.*, vol. 16, no. 5, pp. 3065–3083, 2012, doi: 10.1016/j.rser.2012.02.054.

[4] I. Estiati, F. B. Freire, J. T. Freire, R. Aguado, and M. Olazar, “Fitting performance of artificial neural networks and empirical correlations to estimate higher heating values of biomass,” *Fuel*, vol. 180, pp. 377–383, 2016, doi: 10.1016/j.fuel.2016.04.051.

[5] I. Selvig, WA Wilson, *Calorific value of coal*. New York: Wiley, 1945.

[6] P. Thipkhunthod, V. Meeyoo, P. Rangsunvigit, B. Kitiyanan, K. Siemanond, and T. Rirksomboon, “Predicting the heating value of sewage sludges in Thailand from proximate and ultimate analyses,” *Fuel*, vol. 84, no. 7–8, pp. 849–857, 2005, doi: 10.1016/j.fuel.2005.01.003.

[7] R. García, C. Pizarro, A. G. Lavín, and J. L. Bueno, “Spanish biofuels heating value estimation . Part II : Proximate analysis data,” *Fuel*, vol. 117, pp. 1139–1147, 2014, doi: 10.1016/j.fuel.2013.08.049.

[8] R. García, C. Pizarro, A. G. Lavín, and J. L. Bueno, “Spanish biofuels heating value estimation. Part I: Ultimate analysis data,” *Fuel*, vol. 117, pp. 1190–1198, 2014, doi: 10.1016/j.fuel.2013.08.048.

[9] A. Ozyuguran, S., Yaman, “Prediction of Calorific Value of Biomass from Proximate Analysis,” *Energy Procedia*, vol. 107, pp. 130–136, 2017, doi: 10.1016/j.egypro.2016.12.149.

[10] C. Yin, “Prediction of higher heating values of biomass from proximate and ultimate analyses,” *Fuel*, vol. 90, no. 3, pp. 1128–1132, 2011, doi: 10.1016/j.fuel.2010.11.031.

[11] Y. F. Chang, C. J. Lin, J. M. Chyan, I. M. Chen, and J. E. Chang, “Multiple regression models for the lower heating value of municipal solid waste in Taiwan,” *J. Environ. Manage.*, vol. 85, pp. 891–899, 2007, doi: 10.1016/j.jenvman.2006.10.025.

[12] A. M. Azeez, D. Meier, and J. Odermatt, “Temperature dependence of fast pyrolysis volatile products from European and African biomasses,” *J. Anal. Appl. Pyrolysis*, vol. 90, no. 2, pp. 81–92, 2011, doi: 10.1016/j.jaap.2010.11.005.

[13] S. V Vassilev, D. Baxter, L. K. Andersen, and C. G. Vassileva, “An overview of the chemical composition of biomass,” *Fuel*, vol. 89, no. 5, pp. 913–933, 2010, doi: 10.1016/j.fuel.2009.10.022.

[14] A. O. Balogun, O. A. Lasode, and A. G. McDonald, “Devolatilisation kinetics and pyrolytic analyses of Tectona grandis (teak),” *Bioresour. Technol.*, vol. 156, 2014, doi: 10.1016/j.biortech.2014.01.007.

[15] L. Wilson, W. Yang, W. Blasiak, G. R. John, and C. F. Mhilu, “Thermal characterization of tropical biomass feedstocks,” *Energy Convers. Manag.*, vol. 52, no. 1, pp. 191–198, 2011, doi:

10.1016/j.enconman.2010.06.058.

[16] J. O. Titiloye, M. S. Abu, and T. E. Odetoye, "Thermochemical characterisation of agricultural wastes from West Africa," *Ind. Crop. Prod.*, vol. 47, pp. 199–203, 2013, doi: 10.1016/j.indcrop.2013.03.011.

[17] M. Adjin-tetteh, N. Asiedu, D. Dodoo-arhin, A. Karam, and P. Nana, "Industrial Crops & Products Thermochemical conversion and characterization of cocoa pod husks a potential agricultural waste from Ghana," *Ind. Crop. Prod.*, vol. 119, no. February, pp. 304–312, 2018, doi: 10.1016/j.indcrop.2018.02.060.

[18] A. O. Aboyade *et al.*, "Thermochimica Acta Non-isothermal kinetic analysis of the devolatilization of corn cobs and sugar cane bagasse in an inert atmosphere," *Thermochim. Acta*, vol. 517, no. 1–2, pp. 81–89, 2011, doi: 10.1016/j.tca.2011.01.035.

[19] M. Salaheldeen, M. K. Aroua, A. A. Mariod, S. Foon, and M. A. Abdelrahman, "An evaluation of Moringa peregrina seeds as a source for bio-fuel," *Ind. Crop. Prod.*, vol. 61, pp. 49–61, 2014, doi: 10.1016/j.indcrop.2014.06.027.

[20] M. Kratzeisen and J. Müller, "Suitability of Jatropha seed shells as fuel for small-scale combustion units," *Renew. Energy*, vol. 51, pp. 46–52, 2013, doi: 10.1016/j.renene.2012.08.037.

[21] L. D. Mafu, H. W. J. P. Neomagus, R. C. Everson, M. Carrier, C. A. Strydom, and J. R. Bunt, "Structural and chemical modifications of typical South African biomasses during torrefaction," *Bioresour. Technol.*, vol. 202, pp. 192–197, 2016, doi: 10.1016/j.biortech.2015.12.007.

[22] R. García, C. Pizarro, A. G. Lavín, and J. L. Bueno, "Characterization of Spanish biomass wastes for energy use," *Bioresour. Technol.*, vol. 103, pp. 249–258, 2012, doi: 10.1016/j.biortech.2011.10.004.

[23] M. Hussain, Z. Zhao, J. Ren, T. Rasool, and S. Raza, "Thermo-kinetics and gaseous product analysis of banana peel pyrolysis for its bioenergy potential," *Biomass and Bioenergy*, vol. 122, pp. 193–201, 2019, doi: 10.1016/j.biombioe.2019.01.009.

[24] Y. L. Tan, A. Z. Abdullah, and B. H. Hameed, "Fast pyrolysis of durian (Durio zibethinus L) shell in a drop-type fixed bed reactor : Pyrolysis behavior and product analyses," *Bioresour. Technol.*, vol. 243, pp. 85–92, 2017, doi: 10.1016/j.biortech.2017.06.015.

[25] C. Lisseth *et al.*, "Characterization of residual biomasses from the coffee production chain and assessment the potential for energy purposes," *Biomass and Bioenergy*, vol. 120, pp. 68–76, 2019, doi: 10.1016/j.biombioe.2018.11.003.

[26] D. A. Granados, R. A. Ruiz, L. Y. Vega, and F. Chejne, "Study of reactivity reduction in sugarcane bagasse as consequence of a torrefaction process," *Energy*, vol. 139, pp. 818–827, 2017, doi: 10.1016/j.energy.2017.08.013.

[27] G. Agarwal and B. Lattimer, "Physicochemical , kinetic and energetic investigation of coal – biomass mixture pyrolysis," *Fuel Process. Technol.*, vol. 124, pp. 174–187, 2014, doi: 10.1016/j.fuproc.2014.03.005.

[28] I. Ortiz, M. Marona, Y. Torreiro, J. M. Sánchez-Hervas, M. Fernandez, and R. Pineiro, "Strategy for the Design of Waste to Energy Processes Based on Physicochemical Characterisation," *Waste and Biomass Valorization*, 2019, doi: 10.1007/s12649-019-00631-y.

[29] I. Yakub *et al.*, "Recovery of clean energy precursors from Bambara groundnut waste via pyrolysis : Kinetics , products distribution and optimisation using response surface methodology," *J. Clean. Prod.*, vol. 164, pp. 1430–1445, 2017, doi: 10.1016/j.jclepro.2017.07.068.

[30] B. B. Nyakuma, S. Wong, and O. Oladokun, "Non-oxidative thermal decomposition of oil palm empty fruit bunch pellets : fuel characterisation , thermogravimetric , kinetic , and thermodynamic analyses," *Biomass Convers. Biorefinery*, 2019.

[31] N. A. Nudri *et al.*, "Characterization of oil palm trunk biocoal and its suitability for solid fuel applications," *Biomass Convers. Biorefinery*, 2019.

[32] E. Kethobile, C. Ketlogetswe, and J. Gandure, "Characterisation of the non-oil Jatropha biomass material for use as a source of solid fuel," *Biomass Convers. Biorefinery*, 2019.

[33] M. A. A. Mohammed, A. Salmiaton, W. A. K. G. W. Azlina, and M. S. M. Amran, "Gasification of oil palm empty fruit bunches : A characterization and kinetic study," *Bioresour. Technol.*, vol. 110, pp. 628–636, 2012, doi: 10.1016/j.biortech.2012.01.056.

[34] S. S. Idris, N. A. Rahman, K. Ismail, A. B. Alias, Z. A. Rashid, and M. J. Aris, "Investigation on thermochemical behaviour of low rank Malaysian coal, oil palm biomass and their blends during pyrolysis via thermogravimetric analysis (TGA)," *Bioresour. Technol.*, vol. 101, no. 12, pp. 4584–4592, 2010, doi: 10.1016/j.biortech.2010.01.059.

[35] M. Azim *et al.*, "Microwave-assisted pyrolysis of palm kernel shell : Optimization using response surface methodology (RSM)," *Renew. Energy*, vol. 55, 2013, doi: 10.1016/j.renene.2012.12.042.

[36] W. Wu, Y. Mei, L. Zhang, R. Liu, and J. Cai, "Kinetics and reaction chemistry of pyrolysis and combustion of tobacco waste," *Fuel*, vol. 156, pp. 71–80, 2015, doi: 10.1016/j.fuel.2015.04.016.

[37] C. J. Mulligan, L. Strezov, and V. Strezov, "Thermal Decomposition of Wheat Straw and Mallee Residue Under Pyrolysis," *Energy&Fuels*, vol. 24, pp. 46–52, 2010, doi: 10.1021/ef9004797.

[38] K. A. Motghare, A. P. Rathod, K. L. Wasewar, and N. K. Labhsetwar, "Comparative study of different waste biomass for energy application," *Waste Manag.*, vol. 47, pp. 40–45, 2016, doi: 10.1016/j.wasman.2015.07.032.

[39] T. Aktas, P. Thy, R. B. Williams, Z. Mccaffrey, R. Khatami, and B. M. Jenkins, "Characterization of almond processing residues from the Central Valley of California for thermal conversion," *Fuel Process. Technol.*, vol. 140, pp. 132–147, 2015,

doi: 10.1016/j.fuproc.2015.08.030.

[40] G. Pahla, T. A. Mamvura, F. Ntuli, and E. Muzenda, “Energy densification of animal waste lignocellulose biomass and raw biomass,” *South African J. Chem. Eng.*, vol. 24, pp. 168–175, 2017, doi: 10.1016/j.sajce.2017.10.004.

[41] E. Apaydın-varol and E. Pütün, “Preparation and characterization of pyrolytic chars from different biomass samples,” *J. Anal. Appl. Pyrolysis*, vol. 98, pp. 29–36, 2012, doi: 10.1016/j.jaap.2012.07.001.

[42] S. Liang, Y. Han, L. Wei, and A. G. Mcdonald, “Production and characterization of bio-oil and bio-char from pyrolysis of potato peel wastes,” *Biomass Convers. Biorefinery*, 2014, doi: 10.1007/s13399-014-0130-x.

[43] L. Pattanaik, S. N. Naik, and P. Hariprasad, “Valorization of waste Indigofera tinctoria L . biomass generated from indigo dye extraction process — potential towards biofuels and compost,” *Biomass Convers. Biorefinery*, 2018.

[44] M. K. D. Rambo, F. L. Schmidt, and M. M. C. Ferreira, “Analysis of the lignocellulosic components of biomass residues for biore fi nery opportunities,” *Talanta*, vol. 144, pp. 696–703, 2015, doi: 10.1016/j.talanta.2015.06.045.

[45] A. Abdu and F. L. Inambao, “Characterization of Ugandan biomass wastes as the potential candidates towards bioenergy production,” *Renew. Sustain. Energy Rev.*, vol. 117, p. 109477, 2020, doi: 10.1016/j.rser.2019.109477.

[46] F. S. Akinrinola, N. Ikechukwu, L. I. Darvell, J. M. Jones, and A. Williams, “The potential use of torrefied Nigerian biomass for combustion applications,” *J. Energy Inst.*, no. xxxx, 2020, doi: 10.1016/j.joei.2020.03.003.

[47] M. S. A. Bakar and J. O. Titiloye, “Catalytic pyrolysis of rice husk for bio-oil production,” *J. Anal. Appl. Pyrolysis*, vol. 103, pp. 362–368, 2013, doi: 10.1016/j.jaap.2012.09.005.

[48] S. Sohni, N. A. N. Norulaini, R. Hashim, S. Bahadar, W. Fadhullah, and A. K. M. Omar, “Physicochemical characterization of Malaysian crop and agro-industrial biomass residues as renewable energy resources,” *Ind. Crop. Prod.*, vol. 111, pp. 642–650, 2018, doi: 10.1016/j.indcrop.2017.11.031.

[49] O. A. Lasode, A. O. Balogun, and A. G. McDonald, “Torrefaction of some Nigerian lignocellulosic resources and decomposition kinetics,” *J. Anal. Appl. Pyrolysis*, vol. 109, 2014, doi: 10.1016/j.jaap.2014.07.014.

[50] D. Yadav, L. Barbora, L. Rangan, and P. Mahanta, “Tea Waste and Food Waste as a Potential Feedstock for Biogas Production,” *Environ. Prog. Sustain. Energy*, pp. 1–7, 2016, doi: 10.1002/ep.

[51] S. Naik, V. V Goud, P. K. Rout, K. Jacobson, and A. K. Dalai, “Characterization of Canadian biomass for alternative renewable biofuel,” *Renew. Energy*, vol. 35, no. 8, pp. 1624–1631, 2010, doi: 10.1016/j.renene.2009.08.033.

[52] G. Montero *et al.*, “Higher heating value determination of wheat straw from Baja,” *Energy*, vol. 109, pp. 612–619, 2016, doi: 10.1016/j.energy.2016.05.011.

[53] S. Nanda, P. Mohanty, and K. K. Pant, “Characterization of North American Lignocellulosic Biomass and Biochars in Terms of their Candidacy for Alternate Renewable Fuels,” *Bioenergy Resour.*, vol. 6, pp. 663–677, 2013, doi: 10.1007/s12155-012-9281-4.

[54] S. Nanda, A. K. Dalai, and J. A. Kozinski, “Supercritical water gasi fi cation of timothy grass as an energy crop in the presence of alkali carbonate and hydroxide catalysts,” *Biomass and Bioenergy*, vol. 95, pp. 378–387, 2016, doi: 10.1016/j.biombioe.2016.05.023.

[55] I. Y. Mohammed, Y. A. Abakr, F. Kabir, K. Suzana, and P. Á. B. Á. Characterization, “Effects of Pretreatments of Napier Grass with Deionized Water , Sulfuric Acid and Sodium Hydroxide on Pyrolysis Oil Characteristics,” *Waste and Biomass Valorization*, 2016, doi: 10.1007/s12649-016-9594-1.

[56] H. Cui, S. Q. Turn, T. Tran, and D. Rogers, “Mechanical dewatering and water leaching pretreatment of fresh banagrass , guinea grass , energy cane , and sugar cane : Characterization of fuel properties and byproduct streams,” *Fuel Process. Technol.*, vol. 139, pp. 159–172, 2015, doi: 10.1016/j.fuproc.2015.07.027.

[57] S. Hidayat, M. S. Abu, Y. Yang, N. Phusunti, and A. V Bridgwater, “Characterisation and Py-GC / MS analysis of Imperata Cylindrica as potential biomass for bio-oil production in Brunei Darussalam,” *J. Anal. Appl. Pyrolysis*, vol. 134, pp. 510–519, 2018, doi: 10.1016/j.jaap.2018.07.018.

[58] O. Oladokun *et al.*, “Multicomponent devolatilization kinetics and thermal conversion of Imperata cylindrica,” *Appl. Therm. Eng.*, vol. 105, pp. 931–940, 2016, doi: 10.1016/j.applthermaleng.2016.04.165.

[59] D. De Conto, W. P. Silvestre, C. Baldasso, and M. Godinho, “Performance of rotary kiln reactor for the elephant grass pyrolysis,” *Bioresour. Technol.*, vol. 218, pp. 153–160, 2016, doi: 10.1016/j.biortech.2016.06.082.

[60] H. Viana, D. J. Vega-nieva, L. O. Torres, J. Lousada, and J. Aranha, “Characterization and biomass combustion properties of selected native woody shrub species from central Portugal and NW Spain,” *Fuel*, vol. 102, pp. 737–745, 2012, doi: 10.1016/j.fuel.2012.06.035.

[61] R. K. Mishra and K. Mohanty, “Pyrolysis kinetics and thermal behavior of waste sawdust biomass using thermogravimetric analysis,” *Bioresour. Technol.*, vol. 251, pp. 63–74, 2018, doi: 10.1016/j.biortech.2017.12.029.

[62] S. J. Mitchual, K. Frimpong-mensah, and N. A. Darkwa, “Evaluation of Fuel Properties of Six Tropical Hardwood Timber Species for Briquettes,” *J. Sustain. Bioenergy Syst.*, vol. 4, pp. 1–9, 2014.

[63] M. V Gil, R. García, C. Pevida, and F. Rubiera, “Grindability and combustion behavior of coal and torrefied biomass blends,” *Bioresour. Technol.*, vol.

191, pp. 205–212, 2015, doi: 10.1016/j.biortech.2015.04.117.

[64] M. Phanphanich and S. Mani, “Impact of torrefaction on the grindability and fuel characteristics of forest biomass,” *Bioresour. Technol.*, vol. 102, no. 2, pp. 1246–1253, 2011, doi: 10.1016/j.biortech.2010.08.028.

[65] N. Saikia and M. Bardalai, “Thermal Analysis and Kinetic Parameters Determination of Biomass Using Differential Thermal Gravimetric Analysis in N2 Atmosphere,” *Mater. Today Proc.*, vol. 5, pp. 2146–2156, 2018, doi: 10.1016/j.matpr.2017.09.212.

[66] W. B. Musinguzi, M. A. E. Okure, L. Wang, A. Sebbit, and T. Løva, “Thermal characterization of Uganda’s Acacia hockii , Combretum molle, Eucalyptus grandis and Terminalia glaucescens for gasification,” *Biomass and Bioenergy*, vol. 46, pp. 402–408, 2012, doi: 10.1016/j.biombioe.2012.08.001.

[67] N. Hamzah, M. Zandi, and K. Tokimatsu, “Woody biomass characterization for 100 megawatt-hours (MW) power generation,” *Energy Procedia*, vol. 105, pp. 413–418, 2017, doi: 10.1016/j.egypro.2017.03.334.

[68] R. Sakthivel, K. R. P. Mohamed, and S. R. Purnachandran, “A Complete Analytical Characterization of Products Obtained from Pyrolysis of Wood Barks of Calophyllum inophyllum,” *Waste and Biomass Valorization*, 2018, doi: 10.1007/s12649-018-0236-7.

[69] T. Imam and S. Capareda, “Characterization of bio-oil , syn-gas and bio-char from switchgrass pyrolysis at various temperatures,” *J. Anal. Appl. Pyrolysis*, vol. 93, pp. 170–177, 2012, doi: 10.1016/j.jaap.2011.11.010.

[70] J. Parikh, S. A. Channiwala, and G. K. Ghosal, “A correlation for calculating HHV from proximate analysis of solid fuels,” *Fuel*, vol. 84, pp. 487–494, 2005, doi: 10.1016/j.fuel.2004.10.010.

[71] A. Friedl, E. Padouvas, H. Rotter, and K. Varmuza, “Prediction of heating values of biomass fuel from elemental composition,” vol. 544, no. October 2004, pp. 191–198, 2005, doi: 10.1016/j.aca.2005.01.041.

[72] S. A. Channiwala and P. P. Parikh, “A uni ® ed correlation for estimating HHV of solid , liquid and gaseous fuels q,” vol. 81, 2002.

[73] D. A. Tillman, *Wood as an energy resource*. New York: Academic Press Inc., 1978.

[74] C. Sheng and J. L. T. Ã. Azevedo, “Estimating the higher heating value of biomass fuels from basic analysis data,” vol. 28, pp. 499–507, 2005, doi: 10.1016/j.biombioe.2004.11.008.