Agricultural residue often refers to the residues or by-product of agriculture (Perera *et al*. 2005). The traditional uses for agricultural residues are as follows: as animal feed, soil amendment, and fuel materials (Zeng *et al*. 2007). However, most agricultural residues in China either are left in the wild or are directly combusted, which leads to many problems, including resource waste and environmental pollution (Wang *et al*. 2013b). Therefore, there is increasing attention towards a more rational and efficient use of the residue resources in China (Chen *et al*. 2017). Utilizing agricultural residues would allow for a successful transition from traditional fossil fuels to clean energy. This transition would not only reduce carbon dioxide emissions, but also mitigate resource shortages.

Different types of agricultural residues are abundant and widely distributed in China. It is necessary to evaluate the type, quantity, location, and potential for energy utilization of the different kinds of agricultural residues. Many studies have assessed the amount and distribution of agricultural residue for use as a biomass energy source. For instance, Zeng *et al.* (2017) reviewed the present utilized technologies of straw in biomass energy. Ji (2015) also used an artificial neural network approach to assess the use of agricultural residue resources in China for liquid biofuel production. However, these studies were narrow in scope, assessing a particular resource at an economy-wide level or various resources in a small study area. A comprehensive and detailed assessment of agricultural residue for energy utilization is still missing.

Grey relational analysis (GRA) is a subset of grey system theory, as proposed by Julong Deng in 1982 (Deng 1993). It is used to transform several response variables into a single response function, which means that the multi-objective problem can be converted into a single objective optimization system (Deng 1989). Compared with other mathematical statistics, the GRA technique has a proficient control on the uncertain, incomplete, and multiple information, and it also is unstrained by the distribution of mathematical theory and the sample's capacity (Manikandan *et al*. 2017; Wang *et al*. 2013a; Wang *et al*. 2016a). Grey relational analysis has been widely used for comparing variety, evaluating yield and quality, and screening a diverse set of resources over recent years (Li 2001; Li *et al*. 2001; Niu *et al*. 2017; Yang *et al*. 2017; Jiang *et al*. 2018).

There are currently few reports regarding an evaluation of agricultural residues for energy utilization using grey relational analysis. Given this, the aims of this paper were three-fold: (1) to select the agricultural residues in China and characterize them; (2) to develop a systematic indicator of agricultural residues for energy utilization in China; and (3) to present a GRA method to analyze and evaluate the potential of agricultural residues as feedstock for energy utilization in China. It is hoped that the results presented here will provide a theoretical basis and basic data for the government to formulate and implement relevant policies or strategies of straw energy utilization. Meanwhile, the biomass energy utilization potential evaluation method established in this study will also provide a reference method and basis for other countries or regions to evaluate biomass resources and energy utilization potential.

EXPERIMENTAL

Materials

China's administrative regions

There are 22 provinces, four municipalities, and five autonomous regions in Mainland China. Due to a lack of data, Hong Kong, Macao, and Taiwan will not be included in this analysis. Given its regional differences, Mainland China is further divided into the following six areas: North China, Northeast China, East China, Southcentral China, Southwest China, and Northwest China (Ji 2015), which is the most common method dividing administrative region in China to facilitate data statistics and understand the quantity of straw resources in each region.

Agricultural residue samples

Agricultural residue generally refers to the residues remaining after wheat, rice, maize, rape, cotton, and other crops have been harvested (Wang *et al*. 2013b). The agricultural residues selected for this study are presented in Fig. 1. These residues are representative, and the most common types of residue with relatively large quantities, account for more than 90% of the total resources in China. All agricultural residues were collected during 2015 near the area of Chengdu, China (30.67 °N, 104.06 °E). All residue samples were stored at room temperature to allow for natural drying until constant weights were recorded. The dried biomass samples were ground to a particle size of 1 to 3 mm using a pulverizer and then passed through a standard testing sieve (aperture size, 1.40 mm).

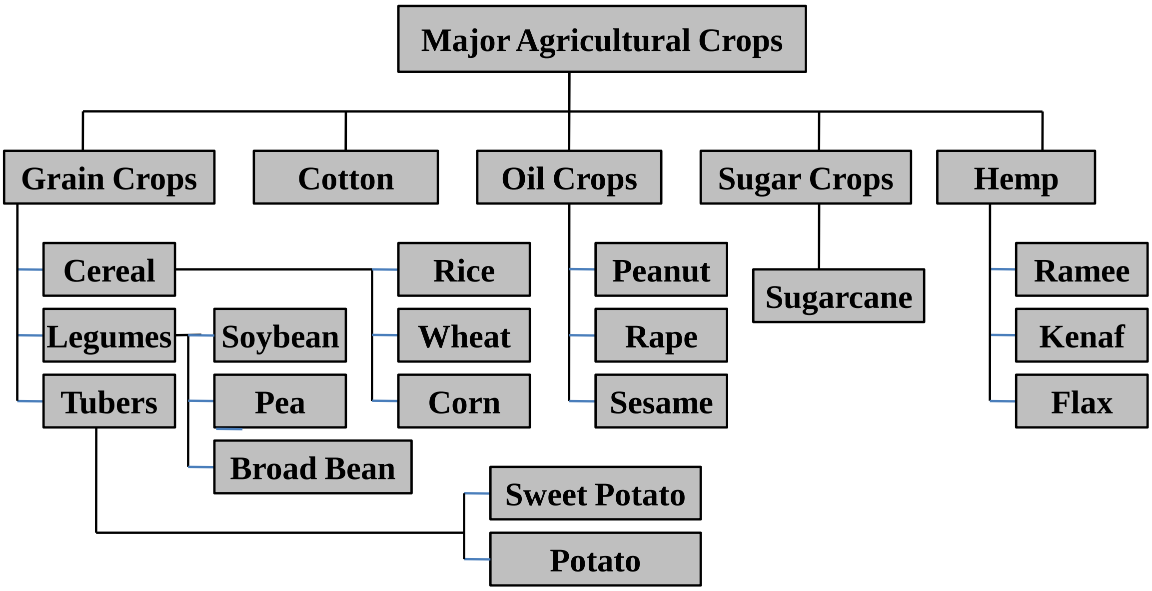

Fig. 1. Major agricultural residues used in this study

Methods

Total output of agricultural residues in China

There are no direct statistics regarding the total output of agricultural residues in China, but it can be estimated from the ratio of crop residue to crop yield, namely residue-to-grain ratio (Table 1) (Ji 2015). The yield of each crop in 2016 was obtained from the Web of China statistical yearbook (National Bureau of Statistics of China 2017). The total output of major agricultural residues was thus obtained using the following equation (Ji 2015): Output of agricultural residue (P) = Crop yield (Y) × Residue-to-grain ratio (I).

Composition content of cellulose biomass of agricultural residue

The contents of cellulose, hemicellulose, and lignin in selected agricultural residues were determined using an FIBERTEC 2010 semi-automatic fiber analyzer (Tecator, Tecator Kjeltec Systems, Hoganas, Sweden), operated according to the manufacturer's instructions and reference (Liu *et al*. 2013).

Table 1. Residue-to-grain Ratios of Various Crops

Major Agricultural Crop			Residue-to-grain Ratio
Grain crops	Cereal	Rice	1.0
		Wheat	1.17
		Corn	2.0
	Legumes	Soybean	1.5
		Pea	1.5
		Broad bean	1.5
	Tubers	Sweet potato	0.5
		Potato	0.71
Cotton			2.91
Oil crops		Peanut	1.14
		Rape	2.87
		Sesame	2.01
Sugar crops		Sugarcane	0.2
Hemp		Ramee	1.9
		Kenaf	1.9
		Flax	1.9

Proximate analysis

Levels of moisture, volatile matter, as well as ash and fixed carbon content were determined using an automatic industrial analyzer (Titen Electronic Co., Ltd., Changsha, China) according to the manufacturer’s instructions. Briefly, each sample was placed into the automatic industrial analyzer and measured in triplicate.

Caloric value

The caloric values for each agricultural residue sample were determined using an oxygen bomb calorimeter IKA C200 (IKA GmbH & Co. KG, Staufen, Germany), in accordance with the test method ASTM D5865-13 (2013). Briefly, a sample pellet of 1.0 g was used for each analysis. A cotton thread was attached to the platinum ignition wire and placed in contact with the pellet. The bomb head (with sample) was then inserted into the bomb cylinder, and then the screw cap was screwed firmly to a solid stop. The bomb was filled with oxygen to a pressure of 30 bars. When the bomb was ready, it was placed into the calorimeter. The bomb was carefully handled to ensure that the sample was not disturbed. Distilled water was filled to the mark into the calorimeter. The calorimeter was then started and run for approximately 26 min. The measured data were displayed through the computer.

CHNSO analysis

The common organic elements (C, H, N, S, and O) were analyzed using a PerkinElmer CHNSO analyzer (PerkinElmer, Inc., Waltham, MA, USA). The sample (1.0 mg) was used in a tin boat assortment to determine the percentage composition of C, H, N, and S; the percentage of O was determined by means of the difference of C, H, N, and S.

Grey relational analysis method

According to the method of GRA, 11 agricultural residues were regarded as a grey system, with each agricultural residue being a grey system factor and the included traits being biomass, cellulose, hemicellulose, lignin, caloric value, and ash. The following steps were applied to determine grey relational grade (GRG) values:

Suppose there was an i data sequence that forms the following matrix:

$$(X_1, \quad X_2, \quad \dots, \quad X_i) = \begin{pmatrix} X_1(1) & \dots & X_1(k) \\ X_2(1) & \dots & X_2(k) \\ \vdots & \vdots & \vdots \\ X_i(1) & \dots & X_i(k) \end{pmatrix}, k = 1,2,\dots,t;\ i = 1,2,\dots n.$$

where k is the sample of the indicator and n is the evaluation object.

Step 1: Determine the reference sequence.

The reference sequence should be an ideal comparison standard, so it is necessary to determine the corresponding traits for the "ideal species" (X_0). Generally, energy production requires lignocellulosic materials with higher biomass, cellulose, hemicellulose, caloric value, and lower lignin and ash, so six factors for the ideal agricultural residue are given the optimal value (best or worst). Other reference data may be used that are based on the evaluation target (Luo *et al*. 2015; Wang *et al*. 2016b). It is defined as:

$$X_0 = (X_0(1), X_0(2), \dots, X_0(k))$$

Step 2: Normalize the raw data.

The raw data must be processed into quantitative indices prior to GRA. Thus, normalizing the raw data from zero to one is indispensable. It is worth noting that a positive indicator occurs when the expected value of the data sequence conforms to the rule "the higher, the better". Similarly, a negative indicator occurs when it conforms to the rule "the smaller, the better". Normalizing can be achieved using Eqs. 1 and 2 (Nelabhotla *et al*. 2016; Wang *et al*. 2016b.

Positive indicator: $$X_i'(k) = \frac{X_i(k) - minX_i(k)}{maxX_i(k) - minX_i(k)} \quad (1)$$

Negative indicator: $$X_i'(k) = \frac{maxX_i(k) - X_i(k)}{maxX_i(k) - minX_i(k)} \quad (2)$$

where $X_i(k)$ is the raw data sequence, $X_i'(k)$ is the normalized data sequence, $maxX_i(k)$ is the maximum of $X_i(k)$, and $minX_i(k)$ is the minimum of the $X_i(k)$.

Step 3: Individually calculate the absolute difference ($\Delta_j(k)$) between each reference sequence and the comparison sequence using Eq. 3:

$$\Delta_i(k) = |X_0'(k) - X_i'(k)| \quad (3)$$

Step 4: Confirm the specific values of M and m,

$$\mathrm{M} = max_{i=1}^{n} max_{k=1}^{t} \Delta_i(k) \qquad \mathrm{m} = min_{i=1}^{n} min_{k=1}^{t} \Delta_i(k)$$

Step 5: Calculate GRC using Eq. 4,

$$\delta_i(k) = \frac{m+\beta M}{\Delta_i(k)+\beta M} \quad (4)$$

where β is the distinguishing coefficient $\beta \in (0,1)$. The smaller the distinguishing coefficient is, the greater the difference between the GRC. To this end, 0.5 is the most widely used and accepted value. Accordingly, the authors have used β = 0.5.

Step 6: Compute the GRG ϱ using Eq. 5,

$$\varrho_i = \frac{1}{t}\sum_{k=1}^{t}\delta_i(k) \tag{5}$$

where ϱ_i is the GRG that reflects the relational degree between the reference sequence and comparison sequence. The larger the value of GRG, the nearer the parameter is to the most favorable optimal setting.

RESULTS AND DISCUSSION

Total Quantity and Distribution of Major Agricultural Residues in China

The distribution of crops is distinct in different regions of China. The reason is that the country has a complex physical geography and social economy. This distribution is an important factor for energy policy framing and efficient utilization of agricultural residues. Information on the total output and geographical distribution of each type of agricultural residue are shown in Fig. 2 and Table 2. The total output of agricultural residues was 941.5 million tons and ranged between 0.5 million tons (0.1%) and 439.1 million tons (46.6%) among rice, wheat, corn, legumes, tubers, hemp, sugarcane, cotton, and other oil crops. Residues of grain crops, including corn (439.1 million tons, 46.6%), rice (207.1 million tons, 21.5%), and wheat (150.7 million tons, 16.0%) were the top three crop residues, accounting for 84.1% of the total selected Chinese agricultural residues. As shown in Fig. 2, the descending order of the total output of agricultural residues was: Corn (439.1 million tons, 46.6%), rice (207.1 million tons, 21.5%), wheat (150.7 million tons, 16.0%), rape (41.7 million tons, 4.4%), legumes (26.0 million tons, 2.8%), sugarcane bagasse (22.8 million tons, 2.4%), peanut (19.7 million tons, 2.1%), tubers (16.8 million tons, 1.8%), cotton (15.4 million tons, 1.6%), sesame (1.3 million tons, 0.1%), and hemp (0.5 million tons, 0.1%).

From Table 2, the total agricultural residue output ranged from 0.5 million tons (Tibet) to 94.0 million tons (Heilongjiang) among the 31 provinces. According to previously defined geographic locations, the 31 provinces were subdivided into six different regions. Here, the largest amount of agricultural residues came from South Central China (220.7 million tons, approximately 23.4%), followed by East China (205.5 million tons, approximately 21.8%), Northeast China (195.0 million tons, approximately 20.7%), North China (131.3 million tons, approximately 14.0%), and Southwest China (111.2 million tons, approximately 11.8%). The three provinces comprising the most abundant agricultural residues are Heilongjiang (94.0 million tons), Henan (91.4 million tons), and Shandong (76.3 million tons), respectively. The corn and wheat residue are the main constituents in Shandong and Henan, which account for about 90% and 82.6% of their total productions. The rice residue mainly came from Northeast (Heilongjiang, 22.6 million tons), Central south (Jiangsu, 19.3 million tons; Jiangxi, 20.1 million tons), and Southwest (Hunan, 26.0 million tons; Hubei, 16.9 million tons). The lowest agricultural residue output was from Northwest China, which only produced 77.8 million tons (approximately 8.3%). This low value was likely due to the region’s sparse population and agriculturally degraded lands. Given the regionally rainy weather, sugarcane bagasse was primarily found in South Central and Southeast China. The amount of cotton straw in Northwest China was 10.6 million tons, accounting for 68.8% of the total output of cotton residue. The output of cotton residue was especially rich in the Xinjiang area and likely due to its special geographical location.

During the process of energy production, economic performance is also an important factor in biofuel production. Yield and distribution have been considered to be the potential cause behind rising raw material cost because of its transportation costs. Thus, residues with a relatively concentrated distribution and higher yield show a better potentiality in energy utilization. Moreover, transportation and harvesting factors should be taken into account. However, in the present study, the data on the distribution is too large. Therefore, it's difficult to take these factors into full account. If the transportation and cost of residue are to be taken into account, more detailed regional distribution characteristics should be studied, such as the theoretical quantity of residues, collectable quantity and usable quantity of residues specific to the city, county or even town level. According to the characteristics and distribution of straw in each town of each county, a relatively concentrated straw collection center should be established in a certain area, and processing enterprises should be reasonably distributed. For example, a radius of 20 to 30 km should be selected as a reasonable area.

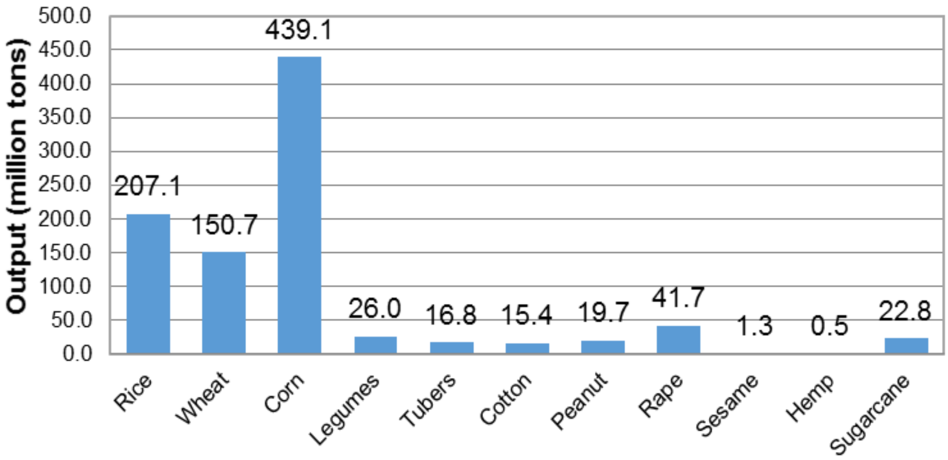

Fig. 2. Major Chinese agricultural residues output by crop category in 2016 (million tons)

Chemical Composition of Major Agricultural Residues

The cellulose, hemicellulose, and lignin contents of all sampled residues ranged from 13.2% to 50.2%, 12.5% to 27.6%, and 1.9% to 13.6%, respectively (Table 3). Regarding cellulose content, the rape, corn and hemp residue contained relatively high levels. These were followed by cotton, rice, legumes, and wheat residue. The cellulose content of tubers and peanut residue were relatively lower when compared with other sampled residues. The wheat, rice, corn residues, and sugarcane bagasse contained higher hemicellulose content, all of which were greater than 20%. The other residues contained lower hemicellulose contents (less than 20%). Because of the high degrees of lignification, the lignin content of hemp residue and sugarcane bagasse ranked first and second, respectively, followed by sesame and rape. The lignin content of rice and wheat residue were lower than those of other residues (1.9% and 3.4%, respectively). It is widely known that greater cellulose and hemicellulose content within crop residue results in a greater benefit to biological fermentation (Pan 2009). Meanwhile, past work has shown that lower lignin content in cellulosic biomass is beneficial to ethanol fermentation and lowering pretreatment costs (Chapple *et al*. 2007). Moreover, the higher lignin contents in agricultural residue result in a greater thermal value. However, higher lignin content is simultaneously bad for gasification (Thomsen *et al*. 2014). Among the sampled residues, the residues of rice, wheat, and corn showed favorable performance, as they had a high content of cellulose (> 30%), hemicellulose (> 20%), and low lignin content (< 6%).

Ultimate Analysis of Major Agricultural Residues

An ultimate analysis of selected agricultural residues was performed using a PerkinElmer (Waltham, MA, USA) CHNSO analyzer and in conjunction with the ASTM D5291-10 (2015) standard.

All results are reported in Table 4; there were no marked differences in C, H, or O content in most samples. This finding underscored the homogeneity in crop residue physicochemical characteristics. All agricultural residues were mainly composed of C and O. It is noteworthy that hemp residue and sugarcane bagasse contained relatively high levels of C and H. Because of the characteristics of the element composition of the structural substance of plants, elements of N and S maintained a low content in all kinds of agricultural residues and it gently fluctuated, ranging from 0.2% to 2.4% and 0.1% to 0.9%, respectively. The organic elemental compositions of wheat, cotton, sesame, and hemp residue, as well as sugarcane were nearly identical. The tubers, peanut, and legumes residue contained slightly higher percentages of N.

The main components of solid fuel are C, H, O, N, and S. In particular, C, H, and O mainly produce CO_2 and H_2O through the exothermic reaction that occurs during combustion. Given this, C, H, and O positively contribute to the energy utilization of agricultural residue. High S content in biomass residue may result in sulfation and the release of Cl (Garcia *et al*. 2012; Telmo *et al*. 2010). Because pollution gases such as NO_X and SO_X are easily produced when burned, the N and S contents in straw biomass are critically important (Vassilev *et al*. 2012; Xiao and Liu 2012). With this in mind, the lower N and S content in straw biomass relative to fossil fuels would be beneficial from an environmental perspective.

Proximate Analysis of Major Agricultural Residues

The results of proximate composition analysis are also shown in Table 4. Both proximate and ultimate analyses served as the basis for a first estimation concerning biomass suitability for exploitation *via* gasification. According to Table 4, the proximate composition of these residues covered a wide range. However, these changes were mostly due to their respective moisture and ash contents. Sesame, peanut, tuber, and rape straws had higher moisture content (> 10.00%) when compared with those of other residues (< 10.00%). Separating the residues from the crop product is closely linked to the moisture contents of agricultural residues (Werther *et al*. 2000).

Significant differences were observed in moisture content of different agricultural residues. Generally the lowest possible moisture content is desirable. Excessive moisture poses problems in firing, such as reducing the combustion temperature, hindering the combustion of reaction products, and consequently damaging the quality of combustion (Chen *et al*. 2009).

According to this study, the ash content of peanut residue was the highest of all the agricultural residues. Rice and tubers had the next highest ash content, while sugarcane bagasse, cotton, and rape residue had the lowest (< 5.00%). Ash is composed of inorganic and mineral elements that crops absorb from the soil, and its content are closely related to combustion characteristics of residue. Leaves generally contain more mineral elements and ash than stalks and other organs, almost twice as much as stalks, so the high ash content in peanuts, rice and tubers residue may be due to the relatively large number of leaves.

It is well known that the presence of ash, especially at high levels, can adversely affect certain processes, such as incineration to generate heat and steam. For residues with high ash content, the ash should be handled in a timely manner as soon as the residues are completely burned. In the process of energy utilization, the residue with high ash content should be expected to a somewhat lower price.

Table 2. Total Output of Major Agricultural Residues in Regions of China in 2016 (10,000 tons)

Region	Rice	Wheat	Corn	Legumes	Tubers	Cotton	Peanut	Rape	Sesame	Hemp	Sugarcane	Total
North China												**13130.42**
Beijing	0.12	10.00	86.38	0.76	0.44	0.02	0.51	0.00	0.01	0.00	0.00	98.22
Tianjin	13.36	71.24	236.20	1.79	0.47	6.78	0.64	0.06	0.01	0.00	0.00	330.55
Hebei	54.72	1676.90	3507.28	48.06	53.17	87.15	147.87	8.89	1.55	0.03	0.00	5585.63
Shanxi	0.49	319.89	1777.78	55.40	24.34	3.00	1.52	2.38	0.44	0.00	0.00	2185.23
Inner Mongolia	63.15	198.78	4279.60	180.00	84.00	0.06	5.58	119.00	0.30	0.31	0.00	4930.79
Northeast China												**19497.27**
Liaoning	484.59	2.57	2931.28	46.05	26.40	0.04	88.63	0.41	0.02	1.89	0.00	3581.88
Jilin	654.10	0.12	5666.00	93.75	26.56	0.00	76.16	0.00	1.36	0.00	0.00	6518.04
Heilongjiang	2255.30	33.95	6254.80	783.78	50.39	0.00	5.43	0.15	0.16	13.38	0.00	9397.35
East China												**22041.32**
Shanghai	81.81	14.15	4.18	0.75	0.05	0.10	0.22	1.99	0.03	0.00	0.11	103.38
Jiangsu	1931.39	1309.88	467.82	108.95	16.40	21.49	41.84	268.64	3.25	0.16	1.80	4171.61
Zhejiang	593.75	29.71	60.90	49.13	31.73	4.81	5.98	65.82	1.83	0.04	12.42	856.11
Anhui	1401.80	1621.50	924.00	202.50	14.95	53.73	103.44	335.30	14.45	4.18	4.05	4679.89
Fujian	471.47	0.64	43.53	36.00	65.41	0.02	32.93	5.59	0.36	0.06	7.40	663.42
Jiangxi	2012.60	3.04	26.00	50.67	37.24	21.33	53.01	206.11	7.44	1.19	13.15	2431.78
Shandong	88.08	2743.17	4129.90	57.56	78.58	159.54	366.57	6.60	0.25	0.08	0.00	7630.32
South Central China												**22068.99**
Henan	542.15	4055.22	3491.84	84.83	56.54	28.37	580.48	234.39	54.73	5.15	4.69	9138.38
Hubei	1693.52	501.02	593.22	43.41	48.36	54.84	81.77	693.48	28.98	3.93	7.47	3749.99
Hunan	2602.30	6.90	377.40	54.75	55.75	35.71	34.88	604.34	3.15	2.57	13.24	3791.00
Guangdong	1087.06	0.35	161.92	33.38	83.61	0.00	127.60	2.55	0.95	0.04	295.86	1793.31
Guangxi	1137.25	1.23	557.14	36.99	38.03	0.74	73.94	8.01	1.53	2.12	1492.26	3349.24
Hainan	149.13	0.00	0.00	3.06	13.32	0.00	12.58	0.00	0.29	0.10	40.92	219.40
Southwest China												**11120.76**
Chongqing	510.55	22.98	529.37	72.56	155.70	0.00	14.03	141.18	1.32	1.41	1.94	1451.05
Sichuan	1558.20	483.68	1586.40	158.70	265.55	2.57	78.39	692.10	0.91	9.92	9.91	4846.33
Guizhou	430.48	69.90	648.76	52.53	150.93	0.35	12.91	259.01	0.12	0.22	23.56	1648.77
Yunnan	671.90	104.60	1513.00	207.99	98.27	0.03	9.38	168.34	0.04	0.09	347.68	3121.32
Tibet	0.51	26.97	5.50	2.24	0.31	0.00	0.04	17.72	0.00	0.00	0.00	53.29

Northwest China												**7781.48**
Shaanxi	91.93	520.69	1090.78	41.46	43.25	9.84	11.86	121.66	3.22	0.14	0.03	1934.85
Gansu	3.12	313.29	1121.12	47.09	113.04	5.79	0.51	98.24	0.00	0.69	0.00	1702.89
Qinghai		38.68	36.14	9.03	18.17	0.00	0.00	85.01	0.00	0.00	0.00	187.03
Ningxia	63.00	47.84	432.32	5.13	17.70	0.00	0.00	0.73	0.00	0.00	0.00	566.73
Xinjiang	59.68	845.98	1369.74	27.89	9.47	1045.80	2.34	26.92	0.09	2.07	0.00	3389.98

Table 3. Chemical Composition of Sampled Major Agricultural Residues

Residue	Content (wt%)		
	Cellulose	Hemicellulose	Lignin
Rice	33.40	27.00	1.90
Wheat	31.07	27.62	3.41
Corn	44.92	24.56	5.29
Legumes	33.40	18.00	8.70
Tubers	16.78	14.15	7.92
Cotton	38.14	13.40	7.96
Peanut	13.18	12.60	11.81
Rape	50.20	18.85	9.46
Sesame	25.58	12.47	11.50
Hemp	42.20	17.80	13.60
Sugarcane	25.68	20.22	12.32

Table 4. Proximate, Ultimate, and Caloric Values of Sampled Major Agricultural Residues

Residue	Proximate Analysis (wt%)				Ultimate Analysis (wt%)					Caloric Value (MJ/kg)
	Moisture	Ash	Volatile Matter	Fixed Carbon	C	H	O	N	S	
Rice	5.60	14.35	66.94	13.11	38.80	5.46	40.65	0.25	0.36	17.19
Wheat	8.79	8.75	69.24	13.22	42.20	5.57	38.64	0.60	0.36	15.94
Corn	6.30	9.50	68.88	15.32	40.66	5.59	39.80	0.22	0.42	17.50
Legumes	7.02	6.17	70.67	16.14	40.49	5.72	41.62	1.13	0.12	15.91
Tubers	10.60	12.50	63.11	13.79	39.00	5.63	37.46	2.39	0.10	15.32
Cotton	7.92	3.73	71.41	16.94	44.63	5.78	43.00	0.66	0.44	15.94
Peanut	10.72	22.71	54.75	11.82	33.56	4.95	31.55	1.54	0.65	12.60
Rape	10.49	4.52	71.16	13.83	43.82	5.97	44.17	0.82	0.85	16.49
Sesame	11.23	6.42	67.89	14.47	41.70	5.78	42.85	0.54	0.52	15.27
Hemp	9.80	6.89	74.30	9.01	45.82	5.92	42.1	0.68	0.11	18.23
Sugarcane	9.06	2.26	74.25	14.43	45.38	5.92	43.73	0.41	0.16	17.46

The volatile matter found in biomass commonly includes CO, CO_2, moisture, hydrocarbon, and tars. The volatile matter contents of all the sampled residues ranged from 54.8% to 74.3%, of which hemp showed the highest percentage of volatile matter and peanut showed the lowest. The fixed carbon content of all agricultural residues were in the range of 9.0% to 16.9%. Cotton, legume, and corn residues contained relatively high levels of fixed carbon (15.3% to 16.9%). These were followed by sesame, sugarcane, rape, tubers, wheat, and rice residues (13.1% to 14.5%). Both hemp and peanut residue had the lowest fixed carbon content. The volatile matter, ash, and fixed carbon contents of wood are approximately 74.7% to 87.1%, 0.3% to 1.5%, and 12.4 to 22.5%, respectively (Telmo *et al*. 2010; Chandrasekaran *et al*. 2013). The respective contents of coal are 28.3% to 37.0%, 7.8 to 22.5%, and 41.0% to 53.5%, respectively (Kim *et al*. 2009; Akkaya 2013). Therefore, the volatile matter content of the sampled agricultural residues was lower than wood, but higher than coal; the ash content was higher than wood, but lower than coal. Finally, the fixed carbon content of the sampled agricultural residues was considerably lower than that of coal.

Caloric Value

An oxygen bomb calorimeter IKA C200 was used to estimate the caloric value of the sampled agricultural residues. The higher the caloric value is, the bigger the potential for the production of bio-energy. The caloric values of the selected residues were between 12.6 MJ/kg and 18.2 MJ/kg. According to Table 4, hemp had a higher heating value than the other crops. This was followed by corn, sugarcane bagasse, and rice. Moreover, wheat had comparable energy content with legumes, tubers, cotton, and sesame. Peanut had the lowest caloric value (12.6 MJ/kg). The caloric value and the contents of lignin and C were positively correlated relationships. The hemp residue had the highest lignin and C content, which may be the reason why the hemp residue has the highest caloric value (Akdenize *et al.* 2004). In general, agricultural residue with a high level of caloric value would be deemed as a better raw material for bioenergy production.

Evaluation of the Potential of Agricultural Residues for Energy Utilization Using GRA

In the current study, the biomass, cellulose, hemicellulose, lignin, caloric value, and ash were used as evaluation indicators. The evaluation sequence X_i was set up with k = 6 and i = 11. The raw data based on the matrix are shown in Table 5; the indicator matrix was established as follows:

$$(X_1,\quad X_2,\quad \dots,\quad X_{11}) = \begin{pmatrix} X_1(1) & \dots & X_1(6) \\ X_2(1) & \dots & X_2(6) \\ \vdots & \vdots & \vdots \\ X_{11}(1) & \dots & X_{11}(6) \end{pmatrix}$$

The reference sequence was as follows:

$$X_0 = (43910.30, 50.20, 27.62, 1.90, 2.26, 18.23)$$

Table 5. Raw Data Evaluating the Energy Potential of Sampled Agricultural Residues

Residue	Biomass (10^4 t)	Cellulose (%)	Hemicellulose (%)	Lignin (%)	Ash (%)	Caloric Value (MJ/kg)
Rice	20707.51	33.40	27.00	1.90	14.35	17.19
Wheat	15074.87	31.07	27.62	3.41	8.75	15.94
Corn	43910.30	44.92	24.56	5.29	9.50	17.50
Legumes	2596.19	33.40	18.00	8.70	6.17	15.91
Tubers	1678.13	16.78	14.15	7.92	12.50	15.32
Cotton	1542.11	38.14	13.40	7.96	3.73	15.94
Peanut	1971.04	13.18	12.60	11.81	22.71	12.60
Rape	4174.62	50.20	18.85	9.46	4.52	16.49
Sesame	126.79	25.58	12.47	11.50	6.42	15.27
Hemp	49.77	42.20	17.80	13.60	6.89	18.23
Sugarcane	2276.49	25.68	20.22	12.32	2.26	17.46

Table 6. Normalization Processed Data

Residue	Biomass	Cellulose	Hemicellulose	Lignin	Ash	Caloric Value
X_1	0.4710	0.5462	0.9591	1	0.4088	0.8153
X_2	0.3426	0.4833	1	0.8709	0.6826	0.5933
X_3	1	0.8574	0.7980	0.7103	0.6460	0.8703
X_4	0.0581	0.5462	0.3650	0.4188	0.8088	0.5879
X_5	0.0371	0.0972	0.1109	0.4855	0.4993	0.4831
X_6	0.0340	0.6742	0.0614	0.4821	0.9281	0.5933
X_7	0.0438	0	0.0086	0.1530	0	0
X_8	0.0940	1	0.4211	0.3538	0.8895	0.6909
X_9	0.0018	0.3350	0	0.1795	0.7966	0.4742
X_{10}	0	0.7839	0.3518	0	0.7736	1
X_{11}	0.0508	0.3377	0.5116	0.1094	1	0.8632

Table 7. Data of Absolute Difference Values

Residue	Biomass	Cellulose	Hemicellulose	Lignin	Ash	Caloric Value
X_1	0.5290	0.4538	0.0409	0	0.5912	0.1847
X_2	0.6574	0.5167	0.0000	0.1291	0.3174	0.4067
X_3	0	0.1426	0.2020	0.2897	0.3540	0.1297
X_4	0.9419	0.4538	0.6350	0.5812	0.1912	0.4121
X_5	0.9629	0.9028	0.8891	0.5145	0.5007	0.5169
X_6	0.9660	0.3258	0.9386	0.5179	0.0719	0.4067
X_7	0.9562	1	0.9914	0.8470	1	1
X_8	0.9060	0	0.5789	0.6462	0.1105	0.3091
X_9	0.9982	0.6650	1.0000	0.8205	0.2034	0.5258
X_{10}	1	0.2161	0.6482	1	0.2264	0
X_{11}	0.9492	0.6623	0.4884	0.8906	0	0.1368

Table 8. Grey Relational Coefficients

Residue	Biomass	Cellulose	Hemicellulose	Lignin	Ash	Caloric Value
X_1	0.4859	0.5242	0.9243	1	0.4582	0.7302
X_2	0.4320	0.4918	1	0.7948	0.6117	0.5514
X_3	1	0.7781	0.7123	0.6331	0.5855	0.7941
X_4	0.3468	0.5242	0.4405	0.4625	0.7234	0.5482
X_5	0.3418	0.3564	0.3599	0.4928	0.4996	0.4917
X_6	0.3411	0.6055	0.3476	0.4912	0.8743	0.5514
X_7	0.3434	0.3333	0.3353	0.3712	0.3333	0.3333
X_8	0.3556	1	0.4634	0.4362	0.8190	0.6180
X_9	0.3337	0.4292	0.3333	0.3786	0.7108	0.4874
X_{10}	0.3333	0.6982	0.4355	0.3333	0.6883	1
X_{11}	0.3450	0.4302	0.5058	0.3596	1	0.7852

The raw data are shown in Table 5. Because each influencing factor had a different meaning and exerted different influence, the interval value transform method was applied to dispose the raw data. The normalization processed data and absolute difference values are presented in Tables 6 and 7, respectively. The GRC and GRG were then calculated using Eqs. 4 and 5 to evaluate the potential for agricultural residues energy utilization. The values of the GRC and GRG are presented in Tables 8 and 9, respectively. The complex process of converting the optimization of multiple processes' variables into the optimization of a single GRG was simplified. According to the theory of GRA, a higher GRC represents a stronger degree between the reference sequence (X_0) and the evaluation sequence (X_i).

According to the results shown in Table 9, corn stover was the most favorable crop according to the grey analysis. The grey relational grades of rice and wheat were 0.6871 and 0.6470, respectively, which were the next best agricultural residues. These were followed by rape, hemp, sugarcane, cotton, legumes, sesame, tubers, and peanut. Although each indicator of the object was not simultaneously reflected to optimize the grey relational grade, the grey relational grade was the optimization of the overall level of the evaluation object. According to these results, corn, rice, and wheat residues had the greatest potential for energy utilization. This finding was based on the comprehensive analysis of all their indicators, which showed the best performance overall. It is know that there are lots of kinds of agricultural crops. The agricultural crops listed in Table 1 are representative, which are the most common crop residues with relatively large quantities, accounting for more than 90% of the total resources in China. Other crop residues represent small portions of the total agricultural crop residues and may not be suitable for energy utilization.

In GRA, experimental data must be preprocessed into quantitative indices prior to use in grey analysis. It's noticeable that the original data dimensionless processing methods depend on the reference sequence and comparison sequence, and the values of correlation degree and weight depend on the number of traits, so attention should be paid to their consistency when carrying out correlation analysis. Meanwhile, some indicators cannot be described quantitatively and there is no accepted standard to determine the optimal value of indicators in the world, which increase the difficulty determining the desirable solution and subjectivity of the comprehensive result.

Table 9. Grey Relational Grades of Sampled Major Agricultural Residues

Residue	Rice	Wheat	Corn	Legumes	Tubers	Cotton	Peanut	Rape	Sesame	Hemp	Sugarcane
GRA	0.6871	0.6470	0.7505	0.5076	0.4237	0.5352	0.3416	0.6154	0.6154	0.4455	0.5710
Rank	2	3	1	8	10	7	11	4	9	5	6

China is a large agricultural country that is rich in agricultural residues. The annual crop yield of China is on the rise. Whether now or in the future, the energy contained in Chinese agricultural residue is huge. The conversion of low-cost, convenient, and huge amounts of agricultural residue into high value-added energy resources has profound significance for solving energy exhaustion and improving the ecological environment. Rice, wheat, and corn are the three main crops; given this, their residues accounted for 84.1% of the total agricultural residues in China in 2016. Different residues have their own, individual way of energy utilization due to their different characteristics. The Chinese government has attached high importance to the development and utilization of biomass as an energy resource. Remarkable results using residues as energy have been obtained in direct combustion, as well as in biochemical and physicochemical conversion. This has included improved stove, biogas, gasification, and briquette formulations (Zeng *et al*. 2007). The main challenge to agricultural residues use as biomass energy is how to develop and manage adequate, affordable, and reliable energy in a sustainable manner that both fuels social and economic development and encourages environmental protection. Different regions in China should be developing residue utilization strategies based on their individual situations and regional technologies to improve the efficient use of stalk resources.

CONCLUSIONS

1. Data obtained from the Web of China statistical yearbook indicated that the most abundant agricultural residue resource in China in 2016 was cereal agricultural residues, which includes corn, wheat, and rice. The lowest agricultural residue yield was hemp. However, there existed considerable differences in regional agricultural residue yields due to geographical differences and farmers' planting habits.
2. The grey relational analysis (GRA) method is suitable for dealing with the optimum solution when using many variables that depend on a desired multi-performance. The resulting GRA revealed that the ideal agricultural residue for energy utilization was corn, with a grey relational grade (GRG) of 0.7505, while the worst residue for energy utilization was peanut residue, with a GRG of 0.3416.
3. The results of comprehensive evaluation on agricultural residues not only provide scientific evidence for their use in energy production, but also provide a reference for the government to further implement a straw utilization strategy.

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Finite Element Modelling of Heat and Moisture Transfer through Cross Laminated Timber Panels

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The primary objective of this research was to assess and to model the hygrothermal properties of CLT panels made from three distinct combinations of spruce lumber and laminated strand lumber (LSL). The hygrothermal performance of these materials both individually and in conjunction in CLT has not been investigated before and is an important indicator of CLT building wall performance. CLT panels consisting of spruce as a face layer absorbed moisture more rapidly when that face layer was exposed to higher moisture concentration compared to CLT panels consisting of LSL as a face layer. The accumulation of moisture between layers increased with placement of the LSL as a core layer. Based on the smaller diffusion coefficient, moisture transport through the CLT panels made of LSL was slower. Modelling with a finite element-based program showed that the temperature in the panels when exposed to a severe gradient equilibrated within two days, as shown by both experimental and simulated results. For moisture transfer, the diffusion coefficient variation with moisture content and temperature based on the Arrhenius equation produced simulation results in agreement with experimental results but the moisture transfer was much slower than the heat transfer.

Keywords: Hybrid Cross laminated timber; Finite element modelling; Hygrothermal

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INTRODUCTION

Cross-laminated timber (CLT) is defined as a prefabricated engineered wood product made of at least three orthogonally bonded lumber layers. Softwoods are usually used for CLT manufacture in North America (Karacabeyli and Douglas 2013). The purpose of this research was to measure both heat and mass transfer through conventional and hybrid CLT panels and to compare the measured data with predictions made using a commercially available finite element modeling program. The mechanical properties and construction techniques of CLT panels have been evaluated extensively, and some hygrothermal data have been reported for CLT panels, but no data exist for the hybrid panel types reported here. Further, given that moisture intrusion is inevitable in wall systems, there is reason to be particularly interested in the potential for moisture accumulation within the panels and whether it could be modeled. Analysis through heat and moisture transfer model will help to prevent issues with buildings in climates that are usually hot or cold and wherever moisture accumulation within wall systems could compromise building integrity. Rapid moisture gain and temperature change are detrimental for energy efficiency and long term durability with respect to moisture related problems.