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Energy conversion of urban wastes in China: insights into potentials and disparities of regional energy and environmental benefits

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Abstract

With the rapid economic growth and urbanization, China is suffering from serious challenges on energy security, and subsequently facing the problems regarding waste treatment and emissions mitigation. Converting urban wastes into energy has been recognized as a promising way to achieve circular economy. In this study, combustible waste, food waste, industrial organic wastewater, and breeding farm manure are considered to be utilized for energy recovery through waste-to-energy (WtE) technologies. Accordingly, four WtE sectors for power generation are formed and introduced into the socioeconomic activities. A methodological framework is established by combining econometrics, physical input-output model and baseline method of clean development mechanism to evaluate the energy and environmental benefits in China's 31 provincial regions during the period 2016-2025. The results reveal that the regions with more waste generation and power generation are Guangdong (11.82 billion kWh in 2025) and Jiangsu (11.43 billion kWh in 2025). Hebei has the largest accumulative mitigation potentials for the emissions of greenhouse gases, sulfur dioxide, nitrogen oxides, and soot and dust (577.57 Mt carbon dioxide equivalent, 1.79 Mt, 0.89 Mt and 16.22 Mt, respectively), followed by Guangdong and Zhejiang. Less developed regions in northwestern China such as Gansu, Qinghai and Ningxia have less energy recovery and mitigation potentials. Meanwhile, the changes in industrial structure contribute to more mitigations in the sectors of power and heat, coal mining, and oil and gas extraction. The quantification of the energy and environmental benefits and revelation of the features and disparities of waste utilization for energy recovery across regions can provide

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insights and managerial implications for better policy-making regarding regional waste management.

Key words: waste; waste-to-energy; physical input-output model; power generation; environmental benefits

1. Introduction

China's continuous economic growth, industrialization and urbanization have been vigorously driving energy consumption for a long time [1]. The energy consumption reached 4.3 billion tons of standard coal equivalent (tce) in 2015 [2], among which 88% is fossil energy that is the primary contributor to global warming and air pollution. As a promising renewable resource, a large number of urban wastes, including municipal solid waste (MSW), industrial organic wastewater (IOWW) and breeding-farm manure (BFM) are being produced due to industrial activities and household consumption, however, only a small proportion of which are recycled and utilized for energy purpose [3]. The Chinese government has been implementing waste sorting in some pilot cities such as Shanghai, which would be beneficial for better resource recycling and energy recovery. Besides, the ambitious goals of carbon reduction (the carbon dioxide emissions of unit GDP should decrease by 60%-65% by 2030 compared with the 2005 level) and pollutant emission reduction (both the emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_x) should decrease by 15% accumulatively during the 13th five-year period) have been proposed. It is of significance to discuss the energy and environmental benefits of utilizing urban wastes for energy recovery, considering the urgency of China to address energy deficiency and accomplish the goal of carbon and pollutant emission reduction.

The most commonly adopted waste disposal methods are sanitary landfill and compost, characterized with low operation difficulty, low investment and cost, but leakage of greenhouse gases (GHGs) and leachate [4,5]. At present, more than 60% of China's MSW is disposed through landfill [2]. Compared with landfill, incineration technology can effectively achieve more than 90% reduction in combustible waste (CW), with the advantages of power and heat generation and reduction in the emissions of GHGs, SO_2, NO_x, and soot and dust (SD) [6]. For food waste (FW), IOWW and BFM, anaerobic digestion is a mature technology widely used to transform the fermentable residues into biogas that can be used for power generation. These waste-to-energy (WtE) technologies have been implemented in many countries, including Australia [7], Japan [8], Switzerland [9] and the U.S. [10]. Numerous studies were conducted to elucidate these benefits of energy-oriented waste utilization through WtE technologies. Yi et al. (2018) listed a summary of previous studies that have discussed the energy recovery and GHG reduction potentials through WtE technologies in diverse countries [11]. Tan et al. (2014) analyzed the energy and carbon reduction potential of different MSW-to-energy strategies in Malaysia [12]. Khalil et al. (2019) highlighted the potential benefits of applying WtE technology via the production of biogas from animal waste as an alternative source of power generation in Indonesia [13]. The quantification of the energy and environmental benefits by these studies verified the importance of waste utilization for energy recovery at the meanwhile.

Despite the renewable nature, the production and utilization of urban wastes involve economic issues and also generate environmental impacts that need to be adequately identified and quantified so that they can be managed more reasonably. Some scholars have carried out relevant studies to analyze the environmental and economic effects induced by waste utilization for energy recovery using various methods such as cost-benefit analysis [14,15], techno-economic analysis [16,17], environmental impact assessment [18,19], life cycle assessment (LCA) [20,21] and input-output (I-O) analysis [22,23]. The economic and environmental effects are closely related to the composition and amount of waste, as well as the type, scale and cost structure of the WtE technologies. He and Lin suggested that waste incineration power generation needs relatively less financial support and perform well on emission reduction [24]. Hamzehkolaei and Amjady found that alternative technology using BFM as fuel instead of traditional technology (electricity from the grid and diesel fuel for heating) to generate electricity are superior, both from economic and environmental point of view. [25].

Among the methods used in the reviewed studies, LCA is a well-established and most widely used one to assess the environmental sustainability of energy systems [26,27]. For instance, Quek et al. evaluated the potential environmental impacts in the transition from fossil fuels-based power generation to 100% renewable power generation throughout various stages in the life cycle of power generation in Singapore, Malaysia and Brunei [28]. Gao et al. analyzed the individual components, locations and environmental impacts of wind and biomass power generation from a life-cycle perspective [29]. In recent years, a great deal of studies are applying I-O models into energy and environmental issues, as they are capable of complementing in the assessment of flows within intricate interactions among industrial activities and final consumption [30-32]. This can be verified by the studies devoted to uncovering the energy use [33-35], CO_2 emissions [36-38], air pollutant emissions [39-41], and water use [42-44] embodied in regional I-O framework. Compared with I-O method, the limitation in the use of LCA and other methods is the difficulty to translate process information into environmental objectives and incorporate environmental and economic issues of the sustainability from sectoral perspective. The physical I-O (PIO) model can better reflect the balance of resource allocation and utilization of various products within an economy compared with the monetary I-O (MIO) model. It could involve the environmental externalities, including wastes generation and consider material recycling which usually has few economic values [30]. The studies by Xu and Zhang [45], Liang and Zhang [46], and Bösch et al. [47] proved the applicability and reliability of PIO model used in the field of waste recycling and energy-oriented utilization.

Although there have been some studies on revealing the environmental and economic impacts of specific WtE technologies using the method such as LCA, few studies have devoted to reflecting the overall energy and environmental benefits of multiple waste categories and waste utilization modes in specific regions. Also, few studies have engaged in PIO modeling for the assessment of the overall benefits of energy-oriented waste utilization. China has significant regional disparity in terms of economic development, technological level and waste utilization potential. Hence the waste utilization strategies in different regions should be formulated more pertinently and flexibly, so as to achieve maximized energy and environmental benefits. Few researchers have ever estimated the potentials of waste generation and assessed the energy and environmental benefits of waste utilization for energy recovery from the perspective of multiple regions in China. We used to carry out studies previously with focus on disclosing the energy and environmental benefits of utilizing urban wastes for energy recovery on city level adopting an I-O model [22,48]. Beyond the previous work, this paper is extended to the whole China to assess the energy and environmental benefits of urban waste utilization through four WtE technologies (CW incineration, FW biogas, IOWW biogas and BFM biogas) in 31 provincial regions. The merits of the PIO model are to be taken advantage of, combined with the baseline method of the Clean

Development Mechanism (CDM) methodology. Regional waste generation potentials, power generation potentials and mitigation potentials for GHG, SO_2, NO_x and SD emissions are to be recognized.

The remaining of the paper is structured as follows: Section 2 describes the formulation of the model for predicting the WtE potentials of CW, FW, IOWW and BFM through four WtE technologies and quantifying the environmental benefits. Section 3 provides specific data as well as some basic information in China's 31 provincial regions adopted in the PIO model and baseline method. The results for 31 regions and some policy implications are presented in Section 4. Finally, the conclusions are drawn in Section 5.

2. Methods

2.1 Structure of the PIO model at provincial level

This study relies on the PIO model which is constructed based on the monetary I-O tables of China's 31 regions [49], following the methodology described by Liang and Wang [22,50]. For the monetary I-O tables, the rows of such a table describe the distribution of a producer's output throughout the economy and the columns describe the composition of the input required by a particular industry to produce its output. However, the PIO model describes physical reality among sectors, in physical units (tons, meters, tons of standard coal-equivalent etc.).

Using the traditional I-O model:

$$x = Ax + y \quad (1)$$

The regional I-O equation can be written in the standard accounting of balance as:

$$x^k = A^k x^k + c^k + s^k + e^k - m^k \quad (2)$$

where x^k is the vector of total output, c^k is the vector of final consumption (i.e. expenditure by household), s^k is the vector of stock changes, e^k and m^k are the vectors of total export and import, respectively. A^k indicates the matrix of intermediate input coefficient and its columns are the input from each industry to produce unit output of each industry. The above conditions hold in each region *k* and each industry.

The emission coefficient of each industry is calculated as the total amount of environmental pressures (including GHGs, SO_2, NO_x and SD emissions) directly produced in an industry divided by the total output of that industry. Using the above formulas, we can explicitly determine the environmental pressures embodied in each industry of a region as:

$$E^{k,p} = f^{k,p}\hat{x}^{k} = f^{k,p}(I - A^{k})^{-1}(\hat{c}^{k} + \hat{s}^{k} + \hat{e}^{k} - \hat{m}^{k}) \quad (3)$$

where *I* is the identity matrix, $f^{k,p}$ is a vector representing environmental pressure *p* of unit output of industries, $E^{k,p}$ is a vector indicating total environmental pressure *p* of industries.

Furthermore, the new WtE sectors are treated as physical multipliers into the PIO model (See **Table 1**), where the matrices Z^k and M^k indicate the intermediate physical input (of general sector's and WtE sectors' products, respectively) from sector *i* to sector *j*. The column vectors y_g^k and y_w^k equal to the sum of column vectors c_g^k, s_g^k, e_g^k and m_g^k, and c_w^k, s_w^k, e_w^k and m_w^k corresponding to general sectors and WtE sectors. The matrices $E_g^{k,p}$ and matrix $E_w^{k,p}$ represent environmental presures of general sectors and WtE sectors. The vectors x_g^k and x_w^k indicate each general sector's and each WtE sector's total output.

2.2 Construction of the PIO model of a provincial region

A PIO model at provincial level is constructed based on Liang and Zhang's method applying PIO tables in Chinese Cities [50]. Similar to the PIO model for Changchun city we conducted in previous study [22], a PIO model for a provincial region is also transformed by the MIO model of the region. Each sector's intermediate deliveries, final consumption, import and export in the PIO model in a region can be calculated by Eqs. (4)-(7).

Table 1. The framework of the physical input-output model

items	Intermediate uses	Final demands				Emissions	Total output
		Final consumption	Export	Stock changes	Import		
Intermediate input	z^k	c_g^k	e_g^k	s_g^k	m_g^k	E_g^k	x_g^k
Physical multipliers	M^k	c_w^k	e_w^k	s_w^k	m_w^k	E_w^k	x_w^k

$$z_{ij}^{k} = z_{ij}^{*k} / x_j^{*k} \times x_j^{k} \quad (4)$$

$$c_i^{k} = c_i^{*k} / x_i^{*k} \times x_i^{k} \quad (5)$$

$$e_i^{k} = e_i^{*k} / x_i^{*k} \times x_i^{k} \quad (6)$$

$$m_i^{k} = m_i^{*k} / x_i^{*k} \times x_i^{k} \quad (7)$$

$$\sum_{j=1}^{n} z_{ij}^{k} + c_{i}^{k} + s_{i}^{k} + e_{i}^{k} - m_{i}^{k} + \sum_{p} E^{k,p} = x_{i}^{k} \quad (8)$$

where z_{ij}^{*k} (z_{ij}^{k}) indicates the monetary (physical) intermediate input from sector i to sector j in a certain region k. x_i^{*k}, c_i^{*k}, e_i^{*k} and m_i^{*k} (x_i^k, c_i^k, e_i^k and m_i^k) are the monetary (physical) total output, final consumption, export and import of sector i, respectively in the region.

In addition, each sector has a global balance, which means that each sector's total input equals to its total output. When the data for intermediate input, final consumption, import and export are obtained through Eqs. (4)-(7), the stock changes can be calculated by Eq. (8). The emissions in each region can be calculated according to each sector's fossil energy consumption and the corresponding emission factors.

The PIO model for a region involves two hypotheses. First, it is assumed that the material intensity matrix of the MIO model and PIO model of the region is the same. Second, future physical I-O relationships among all sectors are assumed to conform to the latest MIO table of the region.

2.3 Accounting of environmental mitigation potentials

The GHG and air pollutant mitigation potentials of four ways of WtE utilization in this study are accounted from two aspects: one is accounted with reference to the baseline method of the CDM methodology; the other is accounted through identifying the changes in the industrial structure based on the PIO tables.

For the first aspect, in 1997 the United Nations climate conference held in Kyoto, Japan adopted the Kyoto protocol that introduced the CDM with the purpose to promote the implementation of GHG reduction projects in the developing countries. The baseline method of the CDM methodology can be used to calculate the GHG emission reduction potentials of power generation projects [51]. In this study, the baseline GHG emissions (BE_y^k) in a region indicate direct emissions from original/traditional treatment of the y-th waste (e.g., landfill for MSW, fermentation for IOWW, septic tank for BFM). The activity GHG emissions (AE_y^k) indicate the emissions from waste utilization for energy recovery through WtE technologies. The difference between these two types of emissions is defined as the mitigation potential for GHG emissions (ME_y^k) as in Eq. (9).

$$ME_y^k = BE_y^k - AE_y^k \quad (9)$$

For the second aspect, waste utilization for power generation in a region can replace traditional power generation using fossil energy. In terms of the I-O framework in the PIO model, the reduction in total output of the power generation sector (due to decrease in traditional power generation) will lead to less intermediate input from other sectors to it. The decrement of total output and intermediate input to the power generation sector from all the sectors can be estimated according to Eq. (2). Thereby the GHG and air pollutant mitigation potentials can be accounted accordingly by Eq. (3).

3. Data presentation

3.1 Study area and sectoral classification

In total 31 provincial regions in China (excluding Taiwan, Hong Kong and Macao) are considered, as coded in **Table 2**. The PIO table is constructed according to the MIO table through aggregation of the sectors (42 sectors aggregated into 24 ones) as illustrated in **Table 3**. The sectors of FFHF, FT, textile, PS and services, as well as household consumption are the sources of four kinds of urban wastes.

Table 2. Study area of 31 provincial regions.

NO.	Regions	NO.	Regions
1	Beijing	17	Hubei
2	Tianjin	18	Hunan
3	Hebei	19	Guangdong
4	Shanxi	20	Guangxi
5	Inner Mongolia	21	Hainan
6	Liaoning	22	Chongqing
7	Jilin	23	Sichuan
8	Heilongjiang	24	Guizhou
9	Shanghai	25	Yunnan
10	Jiangsu	26	Tibet
11	Zhejiang	27	Shaanxi
12	Anhui	28	Gansu
13	Fujian	29	Qinghai
14	Jiangxi	30	Ningxia
15	Shandong	31	Xinjiang
16	Henan		

Table 3. Sectoral classification.

NO.		Sectors	Acronym	Wastes
1	General sectors	Farming, Forestry, Husbandry and Fishery	FFHF	BFM
2		Coal Mining	CM	
3		Oil and Gas Extraction	OGE	
4		Metals Mining	MM	
5		Nonmetals Mining	NMM	
6		Food and Tobacco	FT	IOWW
7		Textile	\	IOWW
8		Timber and Furniture	TF	
9		Papermaking and Stationery	PS	IOWW
10		Petroleum Processing and Coking	PPC	
11		Chemicals	\	
12		Nonmetals	\	
13		Metals	\	
14		Ordinary Machinery	OM	
15		Equipment for Special Purposes	ESP	
16		Transportation Equipment	TE	
17		Electric Equipment and Machinery	EEM	
18		Electronic and Telecommunication Equipment	ETE	
19		Instruments and Meters	IM	
20		Power and heat	PH	
21		Fuel Gas	FG	
22		Water	\	
23		Construction	\	
24		Services	\	CW, FW
25	WtE sectors	CW incineration	WtES1	
26		FW biogas	WtES2	
27		IOWW biogas	WtES3	
28		BFM biogas	WtES4	
29	Final consumption sector	Household consumption	\	CW, FW

3.2 Data on the wastes available for energy recovery

In this study, the MSW contains commercial and household waste, excluding industrial and construction wastes. We assume that the waste components remain constant in the next ten years. It is also assumed that 45% of the MSW is CW that fits incineration for power generation; 35% is FW that can be used for biogas generation; the remainders are neither recyclable (14%) nor suitable for energy recovery (6%) [22,52]. Of all the industrial wastewater, it is assumed that

20% is IOWW, among which only 50% iswith high concentration and suitable for biogas generation [22,53]. For the livestock manure in a region, it is assumed that 30% comes from large breeding farms that can be considered for recycling (the remaining 70% comes from scattered household breeding) [54].

We establish three series of regression relationships among total output of waste source sectors and waste generation amount using unit root test-cointegration test-regression analysis. Three regression relationships are: (a) generation amount of MSW and total output of services sector (household consumption); (b) generation amount of IOWW and total output of the sectors of textile, FT and PS; (c) generation amount of BFM and total output of FFHF sector. The following regression equation is adopted to predict future waste generation amount combined with the PIO tables constructed for each region during 2016-2025.

$$W_y^k = \beta_0^k + \beta_1^k x_{1'}^k + \beta_2^k x_{2'}^k + \cdots + \beta_t^k x_t^k + \varepsilon^k \quad (10)$$

where W_y^k indicates generation amount of the y-th waste (MSW, IOWW or BFM). x_1^k, x_2^k,…, x_t^k denote total output of the waste source sectors (FFHF, FT, textile, PS, services or household consumption). ε^k is a random error. β_0^k, β_1^k,…, β_t^k are regression constants. The regression analysis is carried out using E-views and SPSS.

The data on each sector's physical product yields in a region come from each region's Statistical Yearbook [55]. The annual economic growth rate of each sector is set referring to the 13th five-year plan for each region. The data on monetary import, export, final consumption and total output of a region are obtained from the MIO table 2012 of 31 regions which are the latest ones [49]. The I-O relationships among all sectors in each region within the study period are assumed consistent with those in 2012.

3.3 Data on GHG and pollutant emission coefficients

In this study, GHGs, SO_2, NO_x and SD are selected as the main indicators to illustrate the environmental impacts of waste utilization for energy recovery. NO_x, SO_2 and SD emissions of sectors can be calculated with the data on fossil energy consumption from each region's Statistical Yearbook [55]. The data on GHG emissions of fossil energy consumption of sectors are obtained from the results of Shan et al.'s study [56].

The data on biogas generation coefficients, power generation coefficients and GHG and pollutant emission coefficients of the WtE sectors are listed in **Table 4**. The biogas generation coefficient indicates biogas production from per ton of FW, IOWW or BFM (m^3/t). The power generation coefficient represents power generation from per ton of CW (kWh/t) or from per cubic meter of biogas (kWh/m^3). The biogas generation coefficients of various wastes are calculated by the average corresponding values in the references. The power generation capacity per cubic meter of biogas generated from various wastes is assumed as the same (2 kWh/m^3). The GHG emission coefficient for CW refers to the GHG emissions from incinerating unit amount of CW (429.67 kg/t-CW). As the compositions of biogas after anaerobic digestion of FW, IOWW and BFM are basically the same, GHG emissions of unit power generation by biogas generated from various wastes are assumed as the same (1.27 kg/kWh). The SO_2 and NO_x emissions during the anaerobic fermentation stage are neglected, as SO_2 is desulfurized and the NO_x emission is negligible [57]. Beyond our previous study, we add SD as another major pollutant from CW incineration for power generation. During the whole biogas generation and biogas power generation processes, there are no SD emissions. So we only consider the SD emission coefficient (10 kg/t) for WtES1.

Based on the I-O framework presented in **Table 1** and the sectoral classification presented in **Table 3** combined with the information in **Section 3**, in total 10 (2016-2025) × 31 (provincial regions) = 310 PIO tables could be newly compiled. The details are provided in the **Supplementary data.** Due to a large amount of data, we present the PIO tables (2016 and 2025) of seven typical regions (Beijing, Gansu, Guangdong, Hubei, Jilin, Shandong and Sichuan) as examples.

Table 4. Data on biogas generation coefficients, power generation coefficients and GHG and pollutant emission coefficients.

Waste	Biogas generation coefficients (m^3/t)	Power generation coefficients (kWh/t; kWh/m^3)	GHG emission coefficients (kg/t-CW; kg/kWh)	SO_2 emission coefficients (kg/t; kg/kWh)	NO_x emission coefficients (kg/t; kg/kWh)	SD emission coefficients (kg/t; kg/kWh)	References
CW	-	584.47	429.67	0.65	0.066	10	[58-60]
FW	125.8	2	1.27	0	0	0	[61-63]
IOWW	7.1	2	1.27	0	0	0	[64,65]
BFM	45.6	2	1.27	0	0	0	[67,68]

4. Results

4.1 Wastes available for energy recovery during 2016-2025 in 31 regions

The accumulative amount of CW and FW available for energy recovery in Guangdong is the largest among 31 regions as presented in **Table 5**, amounting to 115.05 Mt and 89.48 Mt, respectively. Hebei and Sichuan have the largest amount of IOWW (3724.89 Mt) and BFM (115.72 Mt), respectively. Located near coast, Zhejiang and Jiangsu have larger accumulative amount of four kinds of wastes. Tibet, Ningxia and Qinghai which are located in the West China have the smallest amount of wastes. Observed overall, the regions with more developed economy and larger population have greater potential of waste resources.

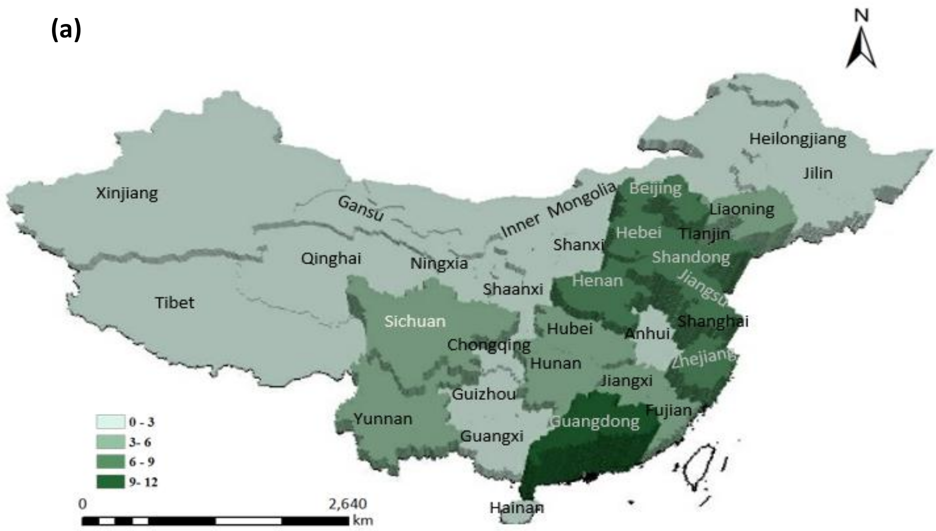
Table 5. Accumulative amount of wastes available for energy recovery during 2016-2025 in 31 regions (Unit: Mt).

Region	CW	FW	IOWW	BFM
Beijing	45.43	35.34	150.18	6.03
Tianjin	13.25	10.31	167.65	5.76
Hebei	32.54	25.31	3724.89	54.28
Shanxi	26.66	20.73	445.95	11.83
Inner Mongolia	18.50	14.39	395.93	16.62
Liaoning	45.77	35.60	814.86	45.00
Jilin	23.67	18.41	447.09	27.08
Heilongjiang	21.55	16.76	367.76	33.60
Shanghai	44.58	34.67	329.41	3.34
Jiangsu	87.58	68.11	1949.85	51.95
Zhejiang	85.83	66.76	1602.28	30.95
Anhui	29.24	22.74	697.84	43.45
Fujian	42.46	33.03	1065.92	32.20
Jiangxi	20.22	15.73	903.56	52.98
Shandong	52.58	40.89	2057.99	76.41
Henan	53.27	41.43	1401.90	115.42
Hubei	39.21	30.50	855.83	73.77
Hunan	35.03	27.25	706.24	97.34
Guangdong	115.05	89.48	1381.48	59.12
Guangxi	25.80	20.06	557.49	55.15
Hainan	12.24	9.52	69.94	11.15
Chongqing	28.31	22.02	242.31	32.15
Sichuan	46.64	36.28	690.14	115.72
Guizhou	17.08	13.28	266.11	33.22
Yunnan	25.51	19.84	497.12	104.64

Tibet	4.07	3.16	3.82	0.92
Shaanxi	28.57	22.22	303.45	20.98
Gansu	12.24	9.52	180.92	13.22
Qinghai	3.98	3.09	89.26	2.92
Ningxia	5.30	4.12	175.74	1.76
Xinjiang	16.87	13.12	322.79	8.11

4.2 Energy recovery from wastes during 2016-2025 in 31 regions

In order to present spatial disparity, the amount of total energy recovery in all regions are presented in **Fig. 1**, resorting to geographical information system (GIS). The regions with the most power generation are Guangdong (10.77 billion kWh in 2016 and 11.82 billion kWh in 2025) and Jiangsu (8.97 billion kWh in 2016 and 11.43 billion kWh in 2025), while Qinghai (0.44 billion kWh in 2016 and 0.49 billion kWh in 2025) and Tibet (0.17 billion kWh in 2016 and 0.49 billion kWh in 2025) have the smallest power generation potentials. Total power generation of all the 31 regions gradually increases during 2016-2025, with the fastest growth rate for Tibet (11.02%), followed by Fujian (5.77%) and Guangxi (5.4%). Such results are inferred by both the historical data of waste generation amount and regional economic development trend.



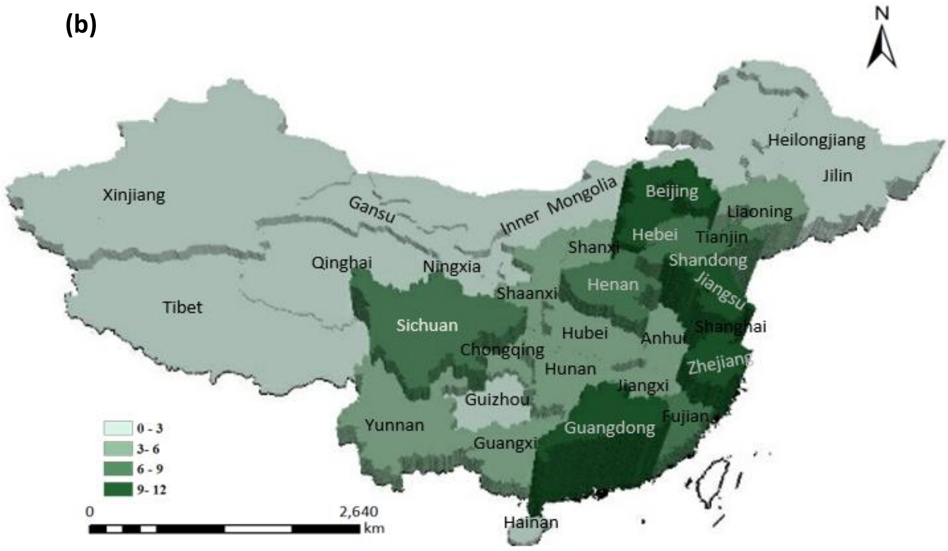


Fig.1. Power generation amount of WtE sectors in 2016 (a) and 2025 (b) in 31 regions (unit: billion kWh)

All the regions are categorized into two levels based upon the proportion of power generation of four WtE sectors. Level 1-regions are those with higher proportion of CW incineration power generation (from WtES1), including 29 regions in 2016 and 28 regions (with change happening to Ningxia) in 2025. CW incineration power generation in these regions accounts for more than 50% in total power generation from waste utilization. It suggests that CW incineration power generation has greater potential among most regions in China. Level 2-regions are those with higher proportion of IOWW biogas power generation (from WtES3), including Hebei and Jiangxi in 2016 and with Ningxia added in 2025. CW incineration power generation keeps the leading position in waste utilization for energy recovery in China owing to larger potential of CW.

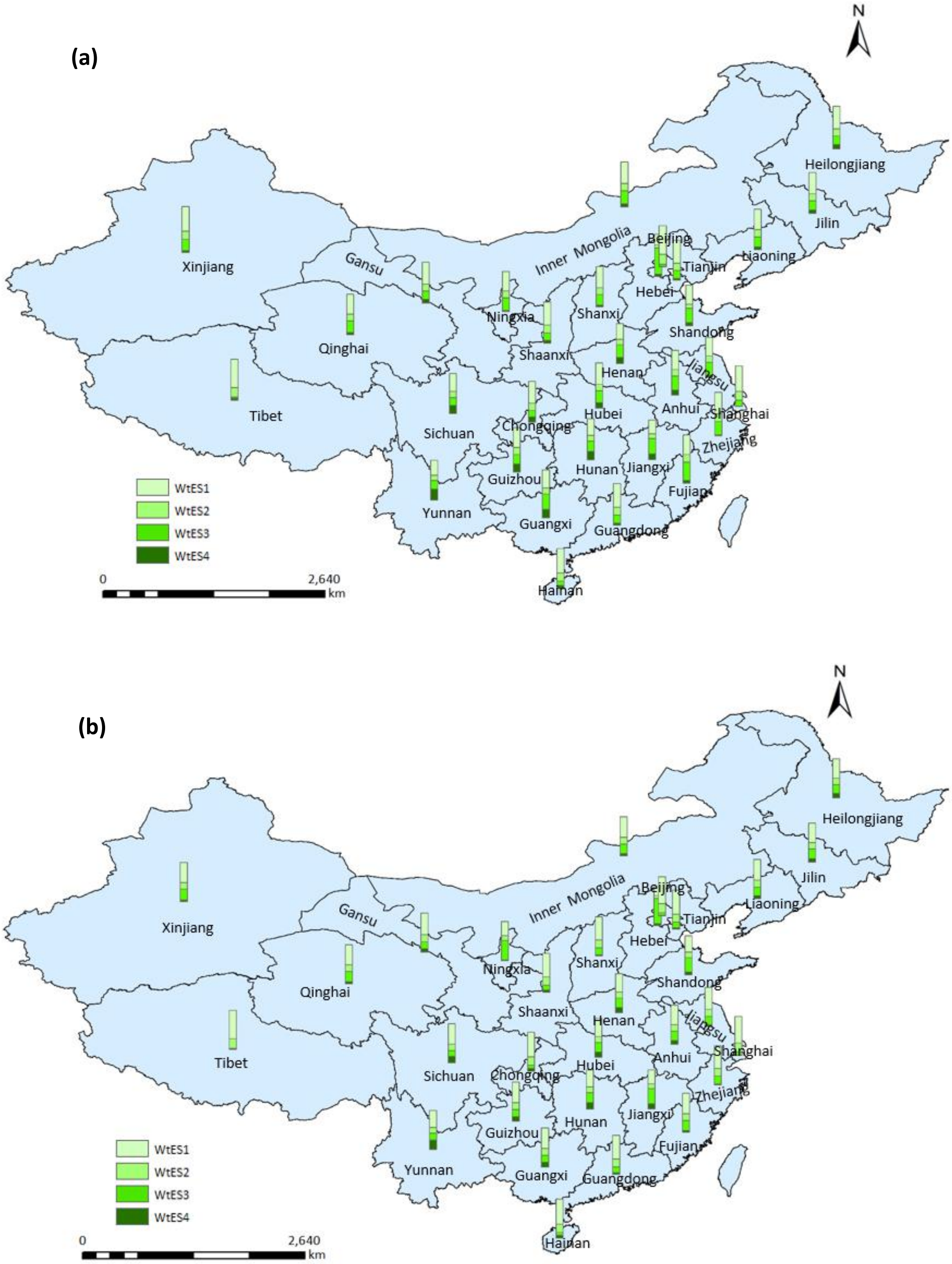


Fig.2. Power generation structure of WtE sectors in 2016 (a) and 2025 (b) in 31 regions (%)

The proportion of biogas power generation (from WtES2, WtES3 and WtES4) in total power generation in each region is depicted in **Fig.3**. It is an important indicator of regional renewable energy development, which is always at a high level in the developed countries. The region with the highest proportion is Beijing (2.24% in 2016 and 3.85% in 2025), whose proportion in 2025 can be close to that in the USA (5% in 2016). Other regions with higher proportion are Hebei, Jiangxi, etc. Most western regions (Xinjiang, Qinghai, Gansu, etc.) have lower potential for biogas power generation.

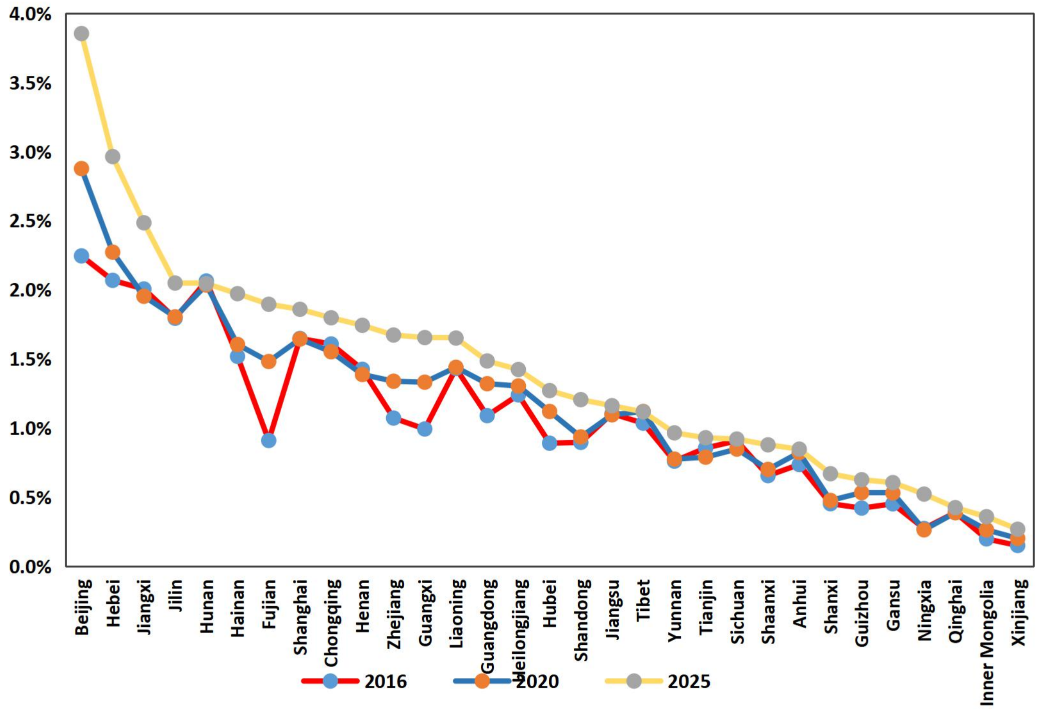


Fig.3. Proportion of biogas power generation in total power generation in 31 regions (2016, 2020 and 2025)

4.3 GHG mitigation potentials by comparison with the baseline during 2016-2025 in 31 regions

The mitigation potentials of WtE sectors for GHG emissions in 31 regions are calculated according to Eq. (9). For WtES2, WtES3 and WtES4, no SO_2, NO_x and SD emissions are generated during either anaerobic fermentation process or biogas power generation process after implementing the disposals of desulphurization, denitration and dust removal. For WtES1, there are SO_2, NO_x and SD emissions, but not significant. Therefore we only focus on GHG mitigation potentials of the WtE sectors by comparison with corresponding baselines.

As illustrated in **Table 6**, the regions with the largest GHG mitigation potential is Hebei (from 43.00 to 61.22 Mt CO_2-e), followed by Henan (from 37.5 to 45.56 Mt CO_2-e) and Jiangsu (from 41.44 to 45.38 Mt CO_2-e). The western regions (Ningxia, Qinghai, Tibet) are also with smaller GHG mitigation potentials. Whereas the growth rate of GHG mitigation potentials in the western regions are larger, (Tibet 9.33% and Ningxia 4.89%), which suggests promising prospects of GHG mitigation from waste utilization in the western regions. The regions of Hainan, Tianjin and Gansu have fewer waste resources, and consequently smaller GHG mitigation potentials.

Table 6. GHG mitigation potentials compared with the baseline in 31 regions of China during 2016-2025 (Unit: Mt CO_2-e).

Region	2016	2020	2025	Region	2016	2020	2025
Hebei	43.00	50.18	61.22	Jilin	12.36	12.92	13.22
Henan	37.50	40.11	45.56	Shanxi	9.91	10.72	13.01
Jiangsu	41.44	43.38	45.38	Heilongjiang	11.55	12.72	12.97
Shandong	39.22	41.10	45.20	Shanghai	11.45	11.98	12.56
Guangdong	41.45	44.37	43.64	Shaanxi	10.28	11.34	12.23
Zhejiang	27.52	36.26	41.60	Beijing	9.06	10.76	12.21
Sichuan	32.09	32.44	33.18	Guizhou	9.13	10.71	11.60
Hunan	27.75	28.94	31.32	Inner Mongolia	7.58	9.67	11.53
Yunnan	22.12	24.65	28.81	Xinjiang	5.65	7.60	8.58
Hubei	21.96	27.12	28.02	Gansu	5.81	6.10	6.04
Fujian	16.33	23.46	26.04	Tianjin	4.87	4.89	5.29
Liaoning	21.88	23.31	24.29	Hainan	3.93	4.53	5.27
Jiangxi	19.07	20.28	22.88	Ningxia	2.64	2.66	4.25
Anhui	15.69	18.79	20.29	Qinghai	1.99	2.06	2.15
Guangxi	14.88	18.48	19.81	Tibet	0.54	0.91	1.30
Chongqing	11.86	12.11	13.27				

The detailed proportions of GHG mitigation potentials in four WtE sectors in each region are further delineated in **Fig. 4**. All the regions are categorized into three levels based upon the proportions. Level 1-regions are those with larger proportion of GHG mitigation potentials contributed by WtES1, including 5 regions (Tibet 55.42%, Beijing 52.98%, Shanghai 44.01%, Tianjin 39.46% and Shaanxi 29.05%). Level 2-regions are those with larger proportion contributed by WtES3, including 15 regions (Hebei 71.18%, Ningxia 58.22%, Shandong 49.36% and so on). Level 3-regions are those with larger proportion contributed by WtES4, including 11 regions (Yunnan 61.16%, Sichuan 52.23%, Hunan 48.72% and so on). For a more densely populous region, it tends to have larger GHG mitigation potential contributed by WtES1. While the regions with more developed light industry (FT, textile and PS) and agriculture generally have larger GHG mitigation potentials contributed by WtES3 and WtES4, respectively.

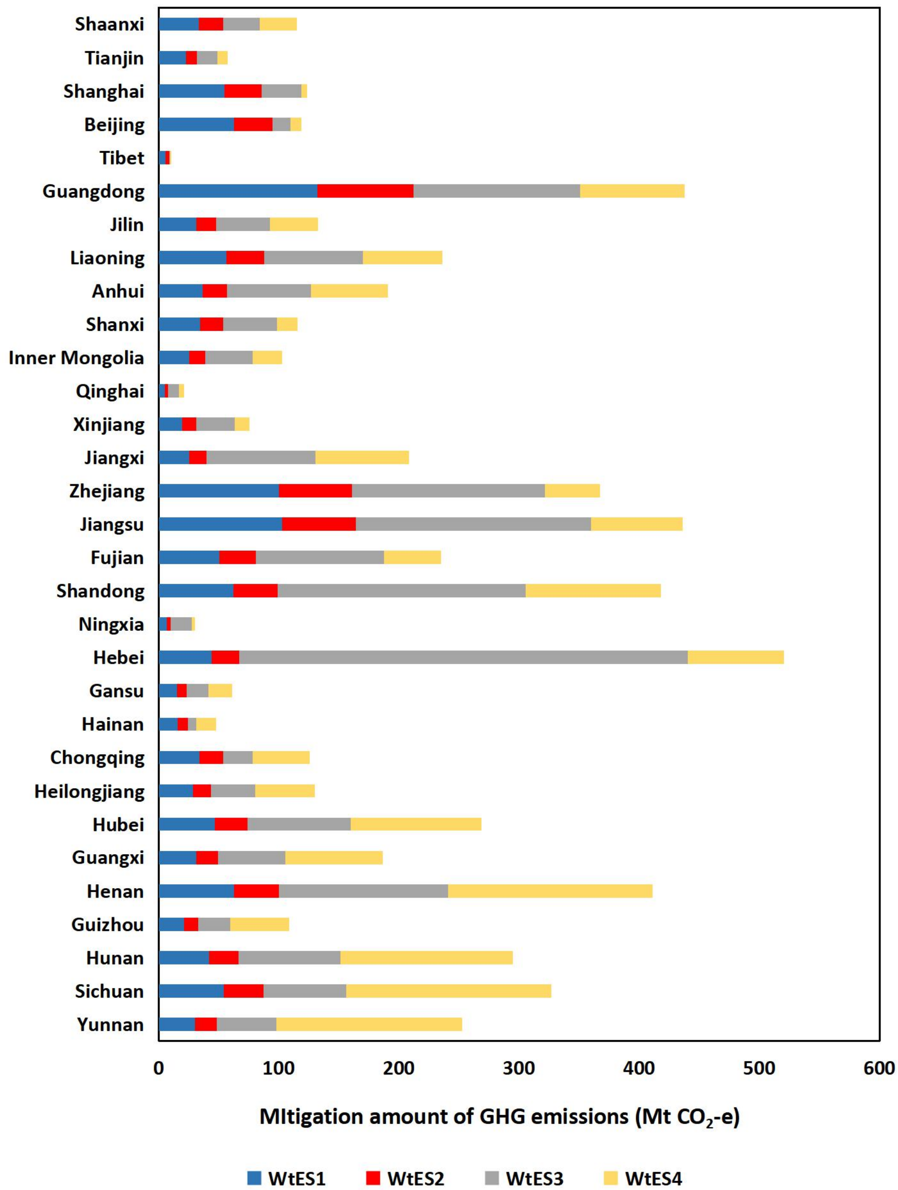


Fig.4. Accumulative GHG mitigation potentials and proportions among four WtE sectors during 2016-2025 in 31 regions

4.4 GHG and air pollutant mitigation potentials contributed by changes in industrial structure during 2016-2025 in 31 regions

Along with the development of WtE Sectors, the intermediate input from the general sectors to power and heat sector in all the 31 regions' PIO models will decrease. Changes in the intermediate input will induce changes in total output of various sectors, and indirectly affect GHG and pollutant emissions. In addition, as there is no energy balance sheet in the Tibet's statistical yearbook, Tibet is not included in this part.

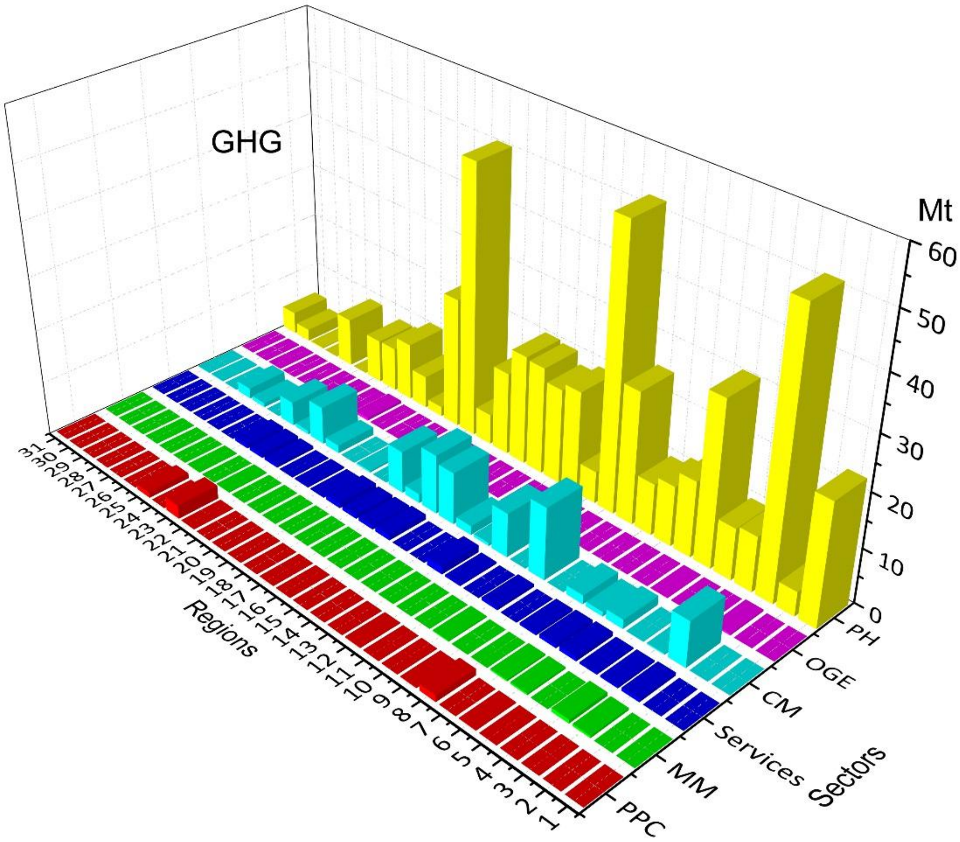
The region with the largest GHG mitigation potential is Hebei (7.50 Mt CO_2-e in 2025) (see), followed by Zhejiang and Guangdong. Overall the mitigation potentials for GHG emissions are estimated from two dimensions: accounted through comparison with the baseline and identification of changes in industrial structure. Hebei has the largest GHG mitigation potential (598.36 Mt accumulatively during 2016-2025) from both two dimensions, followed by Guangdong and Jiangsu. The largest air pollutant mitigation potentials also appear to Hebei (mitigation potentials of SO_2, NO_x and SD emissions are 0.23 Mt, 0.11 Mt, 2.05 Mt in 2025, respectively), followed by Anhui and Zhejiang. The western regions have smaller mitigation potentials (in accordance with the mitigation potentials compared with the baseline).

Among the 24 general sectors, we picked up six of them with larger mitigation potentials, including the sectors of coal mining (CM), oil and gas extraction (OGE), metals mining (MM), petroleum processing and coking (PPC), power and heat (PH) and Services. As depicted in **Fig. 5**, PH sector has the largest GHG mitigation potential among the six, with the largest potential for Zhejiang (52.03 Mt CO_2-e). Jiangsu and Sichuan have the largest GHG mitigation potentials in CM sector (13.36 Mt CO_2-e) and OGE sector (0.54 Mt CO_2-e), respectively. Sichuan and Fujian have the largest potentials in PPC sector and services sector, respectively. The mitigation potentials for SO_2, NO_x and SD have the same trends among sectors. PH sector also has the largest air pollutant mitigation potentials with the largest for Zhejiang (15.65Mt, 7.83Mt and 14.19Mt, respectively for three pollutants). Anhui has the largest potentials in CM sector (1.19 Mt, 0.60 Mt and 10.80 Mt). As for MM and services sectors, Shanxi and Fujian have the largest potentials, respectively. Seen overall, the amount of wastes available for energy recovery and regional industrial structure (represented by the intermediate input matrix) determine the mitigation potentials in sectors of a region.

Table 7. GHG and air pollutant mitigation potentials contributed by changes in industrial structure in 2016 and 2025 in 31 regions.

Region	GHG (Mt CO_2-e)		SO_2 (kt)		NO_x (kt)		SD (kt)	
	2016	2025	2016	2025	2016	2025	2016	2025
Beijing	1.76	2.38	18.69	26.78	9.35	13.40	169.35	242.42
Tianjin	0.43	0.52	0.54	0.83	0.30	0.47	5.37	8.59
Hebei	4.95	7.50	148.85	225.71	74.42	112.85	1349.54	2046.41
Shanxi	0.95	1.55	10.88	23.27	5.44	11.64	98.63	211.00

Inner Mongolia	0.79	1.29	4.06	9.21	2.03	4.62	36.87	83.75
Liaoning	3.09	3.66	103.82	139.84	51.91	69.93	941.34	1268.00
Jilin	1.53	1.67	98.34	141.29	49.18	70.66	891.78	1281.26
Heilongjiang	1.42	1.53	13.98	16.91	6.99	8.46	126.75	153.35
Shanghai	0.88	1.08	26.58	32.37	13.29	16.19	240.96	293.49
Jiangsu	3.17	4.88	3.83	8.04	3.16	5.63	20.08	52.86
Zhejiang	3.96	6.38	119.17	191.96	59.59	95.98	1080.51	1740.44
Anhui	1.01	1.93	92.73	207.35	46.37	103.68	840.77	1880.00
Fujian	1.39	2.66	33.50	73.55	16.75	36.79	303.59	666.26
Jiangxi	1.73	2.29	49.69	84.46	24.85	38.99	450.56	765.81
Shandong	2.99	3.71	23.88	34.88	11.94	17.44	216.53	316.23
Henan	2.54	4.30	48.26	94.52	24.13	47.26	437.60	856.99
Hubei	1.53	2.03	34.41	52.54	17.21	26.27	311.99	476.40
Hunan	1.20	1.69	48.89	76.29	24.45	38.15	443.37	691.79
Guangdong	4.80	5.36	39.04	50.69	14.64	19.01	353.92	459.57
Guangxi	1.80	3.10	6.50	14.03	3.25	7.01	58.93	127.19
Hainan	0.16	0.26	2.93	5.40	1.46	2.70	26.55	49.00
Chongqing	0.61	1.03	45.93	123.33	22.96	61.66	416.42	1118.19
Sichuan	1.80	2.73	37.71	48.82	18.86	24.41	341.92	442.60
Guizhou	0.71	1.23	4.95	13.18	2.47	6.59	44.86	119.54
Yunnan	1.07	2.04	17.97	35.12	9.00	17.60	163.24	319.12
Tibet	-	-	-	-	-	-	-	-
Shaanxi	0.84	1.18	34.27	65.29	17.14	32.64	310.74	591.92
Gansu	0.22	0.40	19.15	35.07	9.57	17.54	173.59	318.01
Qinghai	0.03	0.05	0.69	1.35	0.35	0.67	6.26	12.23
Ningxia	0.22	0.31	2.70	4.05	1.35	2.03	24.46	36.74
Xinjiang	0.36	0.49	2.12	3.70	1.06	1.85	19.19	33.55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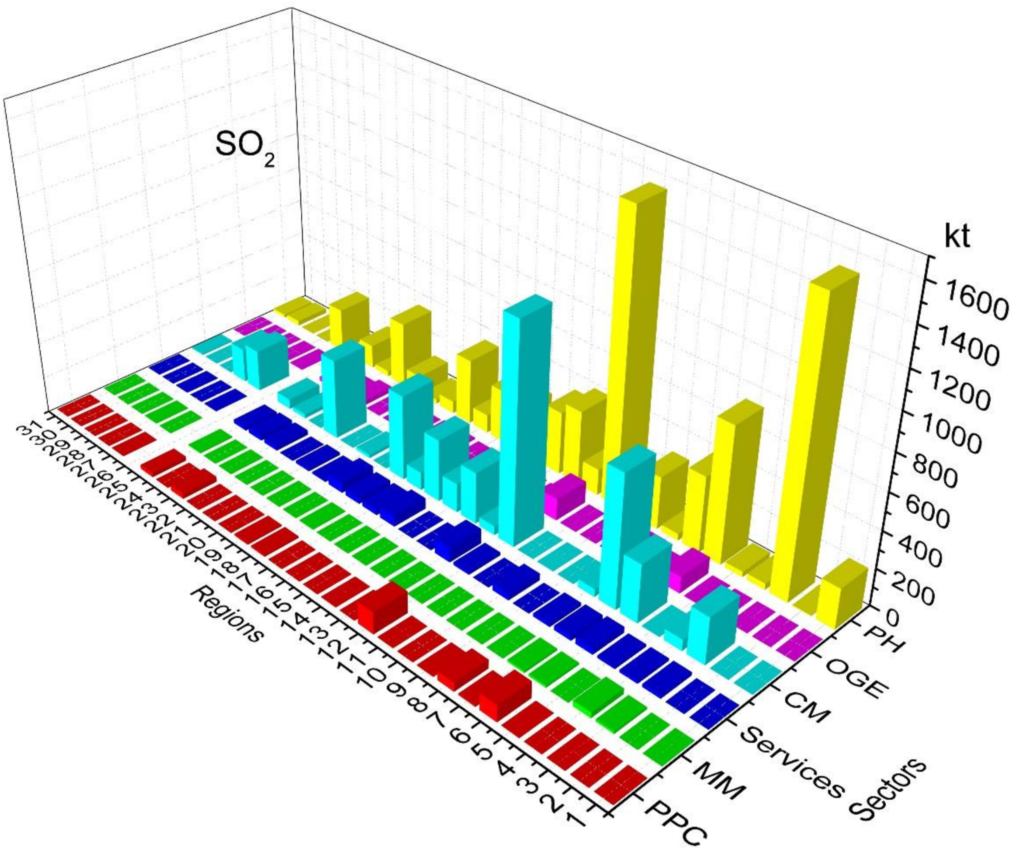
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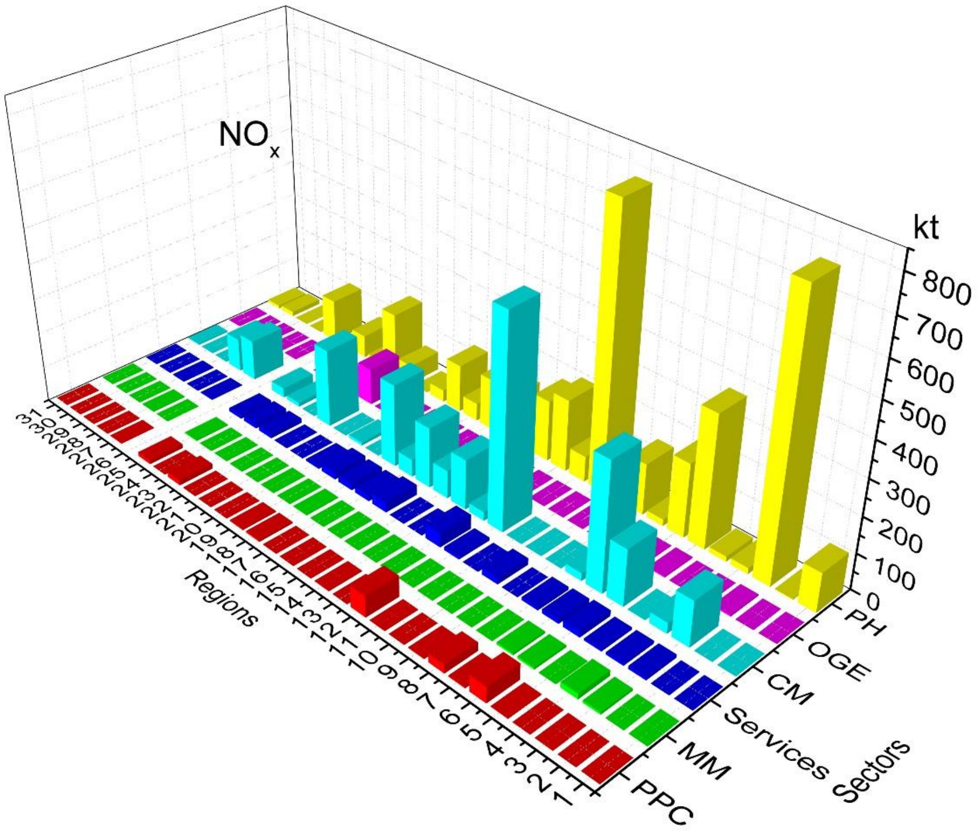

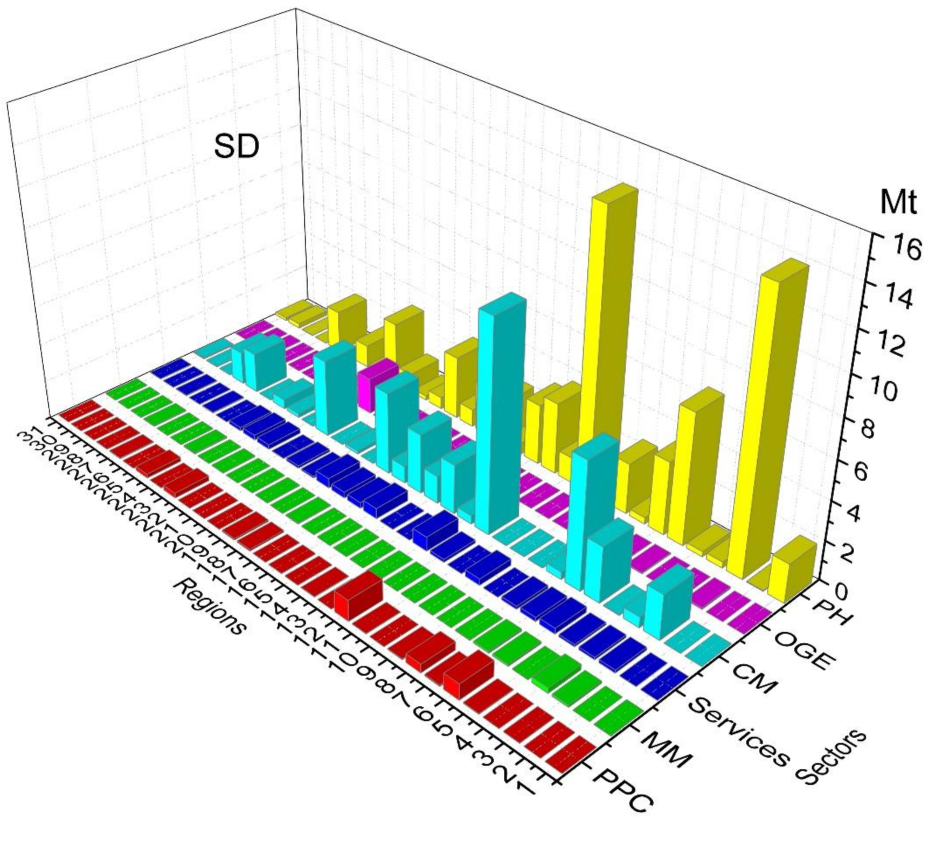

Fig.5. Accumulative GHG and air pollutant mitigation potentials in some of the general sectors during 2016-2025 in 31 regions (PPC denotes petroleum processing and coking, MM donates

metals mining, CM denotes coal mining, OGE denotes oil and gas extraction, PH demotes power and heat)

4.5 Results in some additionally set scenarios

In order to reflect the capabilities of the model system established and better strengthen the results, we additionally design two scenarios where changes in power displacement and economic growth rate of the waste source sectors.

Originally, we set 100% power displacement, assuming that all power generation from the WtE sectors will displace traditional power. In this case, the estimated mitigation potentials are maximized to the largest extent. Whereas 100% displacement cannot be attained practically. Hereby we set 80% power displacement to explore the impacts of change in power displacement on the accumulative mitigation potentials of emissions. The results are presented in **Table 8**. As power displacement induces changes in industrial structure without impacts on the comparison with the baseline, only the mitigation potentials contributed by changes in industrial structure are affected. Lower power displacement inevitably leads to smaller mitigation potentials.

Table 8. Accumulative GHG and air pollutant mitigation potentials under different power displacement rate (2016-2025).

Region	100% power displacement				80% power displacement			
	GHG (Mt CO_2-e)	SO_2 (kt)	NO_x (kt)	SD (kt)	GHG (Mt CO_2-e)	SO_2 (kt)	NO_x (kt)	SD (kt)
1	141.34	228.74	114.44	2071.39	136.77	199.55	99.83	1807.24
2	61.74	6.37	3.59	65.11	60.83	5.09	2.87	52.09
3	581.28	1789.26	894.63	16222.62	569.06	1471.32	735.66	13339.93
4	127.26	155.03	77.51	1405.57	124.93	124.02	62.01	1124.45
5	112.79	62.12	31.13	564.44	110.75	49.69	24.90	451.55
6	269.74	1201.92	601.02	10898.53	262.98	963.56	481.83	8737.15
7	148.26	1190.96	595.57	10799.67	145.05	952.77	476.46	8639.74
8	144.43	148.64	74.34	1348.02	141.53	118.92	59.47	1078.41
9	133.30	291.95	145.97	2646.98	131.36	233.56	116.78	2117.58
10	475.22	55.96	42.05	337.42	467.42	44.76	33.64	269.93
11	419.17	1569.86	784.93	14233.43	408.73	1255.89	627.95	11386.74
12	205.48	1462.07	731.03	13256.06	202.56	1179.06	589.53	10690.16
13	255.95	539.32	269.76	4886.18	251.74	434.05	217.11	3932.50
14	227.72	629.45	311.49	5707.04	223.84	503.56	249.19	4565.63
15	448.18	260.86	130.43	2365.13	442.12	208.69	104.34	1892.11
16	443.18	662.27	331.14	6004.59	436.70	529.82	264.91	4803.67

17	286.59	435.89	217.95	3952.19	282.97	348.71	174.36	3161.75
18	309.04	620.90	310.50	5650.32	306.16	496.72	248.40	4520.26
19	489.21	448.85	168.32	4069.53	478.90	359.56	134.83	3259.97
20	211.50	100.34	50.17	909.72	206.52	80.27	40.13	727.78
21	49.86	39.72	19.86	360.16	49.45	31.78	15.89	288.13
22	133.23	762.27	381.13	6911.22	131.67	609.81	304.90	5528.98
23	348.62	423.73	211.86	3841.79	344.26	338.98	169.49	3073.43
24	118.24	85.29	42.64	773.26	116.31	68.23	34.11	618.61
25	267.01	248.77	124.64	2260.08	264.08	199.02	99.71	1808.07
26	10.46	-	-	-	10.46	-	-	-
27	124.83	484.55	242.27	4393.21	122.82	387.64	193.82	3514.57
28	64.14	269.36	134.68	2442.18	63.52	215.49	107.74	1953.75
29	21.48	9.75	4.87	88.37	21.40	7.80	3.90	70.70
30	32.70	30.92	15.46	280.35	32.21	24.74	12.37	224.28
31	79.70	28.92	14.46	262.20	78.82	23.13	11.57	209.76

The annual economic growth rate of each sector is set referring to the 13th five-year plan for each region. Given the regression coefficients, waste generation amount is closely related to total output of the waste source sectors. **Table 9** presents the impacts of 5% increase in the growth rate of total output of the waste source sectors on the accumulative mitigation potentials of emissions. For the first dimension of mitigation, increase in the growth rate leads to more waste generation and thus larger mitigation potentials compared with the baseline (reflected by difference of accumulative GHG mitigation potentials). For the second dimension of mitigation, increase in the growth rate leads to more emissions of these sectors, which offset the mitigations due to changes in industrial structure (more waste → more power generation and power displacement → change in industrial structure) to some extent. Thus increase in the growth rate of the waste source sectors does not induce remarkable change in the mitigation potentials, especially for pollutant emissions.

Table 9. Accumulative GHG and air pollutant mitigation potentials under different growth rate of total output of the waste source sectors (2016-2025).

Region	Growth rate according to governmental plan				Growth rate 5% higher than that in the governmental plan			
	GHG (Mt CO_2-e)	SO_2 (kt)	NO_x (kt)	SD (kt)	GHG (Mt CO_2-e)	SO_2 (kt)	NO_x (kt)	SD (kt)
1	141.34	228.74	114.44	2071.39	145.13	249.44	124.79	2259.05
2	61.74	6.37	3.59	65.11	64.60	6.37	3.59	65.11

3	581.28	1789.26	894.63	16222.62	605.63	1839.14	919.57	16674.91
4	127.26	155.03	77.51	1405.57	133.04	155.03	77.51	1405.57
5	112.79	62.12	31.13	564.44	117.92	62.12	31.13	564.44
6	269.74	1201.92	601.02	10898.53	281.47	1204.44	602.29	10921.44
7	148.26	1190.96	595.57	10799.67	154.87	1190.96	595.57	10799.67
8	144.43	148.64	74.34	1348.02	150.92	148.64	74.34	1348.02
9	133.30	291.95	145.97	2646.98	139.48	291.95	145.97	2646.98
10	475.22	55.96	42.05	337.42	497.03	55.96	42.05	337.42
11	419.17	1569.86	784.93	14233.43	437.52	1569.86	784.93	14233.43
12	205.48	1462.07	731.03	13256.06	214.95	1473.83	736.91	13362.70
13	255.95	539.32	269.76	4886.18	267.54	542.56	271.38	4915.62
14	227.72	629.45	311.49	5707.04	238.14	629.45	314.73	5707.04
15	448.18	260.86	130.43	2365.13	469.07	260.86	130.43	2365.13
16	443.18	662.27	331.14	6004.59	463.72	662.27	331.14	6004.59
17	286.59	435.89	217.95	3952.19	300.02	435.89	217.95	3952.19
18	309.04	620.90	310.50	5650.32	324.44	650.72	325.40	5920.66
19	489.21	448.85	168.32	4069.53	511.08	449.44	168.54	4074.97
20	211.50	100.34	50.17	909.72	220.88	100.54	50.27	911.54
21	49.86	39.72	19.86	360.16	52.26	40.22	20.11	364.64
22	133.23	762.27	381.13	6911.22	139.50	762.27	381.13	6911.22
23	348.62	423.73	211.86	3841.79	364.96	423.73	211.86	3841.79
24	118.24	85.29	42.64	773.26	123.72	85.63	42.81	776.34
25	267.01	248.77	124.64	2260.08	279.63	248.77	124.64	2260.08
26	10.46	-	-	-	10.98	-	-	-
27	124.83	484.55	242.27	4393.21	130.57	484.55	242.27	4393.21
28	64.14	269.36	134.68	2442.18	67.65	308.97	154.48	2801.32
29	21.48	9.75	4.87	88.37	22.54	9.75	4.87	88.37
30	32.70	30.92	15.46	280.35	34.22	30.92	15.46	280.35
31	79.70	28.92	14.46	262.20	83.46	28.92	14.46	262.20

5. Discussion

Development of the waste source sectors (FHFF, FT, textile, PS and services), as well as the population, household consumption and GDP of a region collectively affect the amount of wastes available for energy recovery. The information of population, household consumption and GDP of 31 regions in 2016 is depicted in **Fig.6** (the clockwise order is according to regional WtE potentials). The eastern regions (Guangdong, Jiangsu, Zhejiang) tend to have larger values for population, household consumption and GDP, while the western regions (Gansu, Ningxia, Qinghai) tend to have the opposite conditions. This is basically consistent with the results of regional WtE potentials and mitigation potentials of emissions. The region with the highest WtE potential per capita is Shanghai (150.15 kWh per capita), followed by Beijing (149.95 kWh per capita) and Zhejiang (125.76 kWh per capita). This suggests better WtE potential per capita for the economically developed regions.

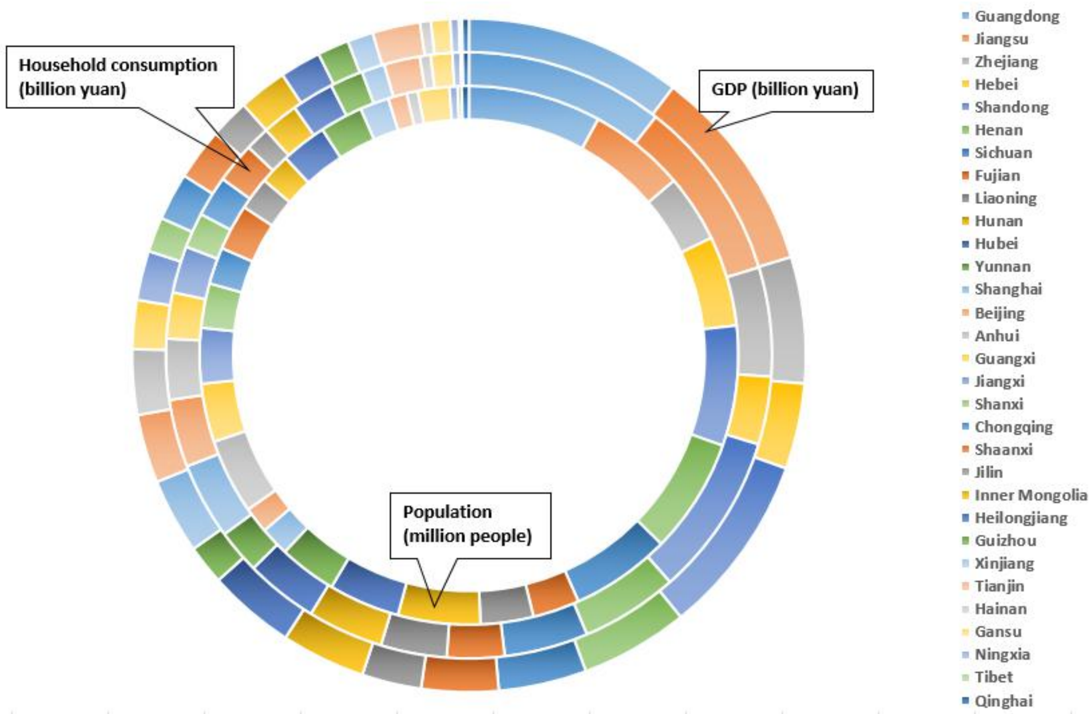

Fig.6. Structure of population, household consumption and GDP of 31 regions in 2016

According to the historical data, the relationships between waste generation amount and total output of the waste source sectors can be investigated by regression analysis. Owing to the future time-sequence PIO tables constructed involving predicted total output of sectors for each region, regional waste generation amount can be forecast. Overall, waste generation amount in each region is in line with regional economic development trends. The proportions of power generation from four kinds of wastes are different across regions. Most regions are those with higher proportion of CW incineration power generation (from WtES1). Two dimensions of mitigation potentials for GHG and air pollutant emissions are accounted. The GHG mitigation potentials by comparison with the baseline are affected by waste generation amount combined with waste structure. Besides waste power generation amount, the mitigation potentials contributed by changes in industrial structure are further affected by regional industrial structure, reflected by the input from other sectors to the PH sector.

The PIO model reflects the interrelationships among various products during production processes, which are basically determined by technological conditions of production. Therefore, the PIO model is capable of presenting the technological connections among the products of socioeconomic activities precisely, without being affected by price variations and variance of price from value. The new PIO tables for 31 regions are constructed based on corresponding MIO tables (in 2012), where fixed production structure of sectors, constant returns to scale and constant prices of commodities and services are assumed within the study period (2016-2025). During the process of transforming the MIO tables into PIO tables, the output of many sectors cannot be quantified. For example, the total output of the services sector only includes a small part that can be quantified, resulting in that the total output as well as emissions of sectors are relatively conservative. The above may lead to impacts on the overall industrial structure and future GHG and pollutants emissions. Future updated I-O tables should make difference with this regard.

Due to a large quantity of data input, the results of this study are primarily affected by some major parameters. Hereby a parametric analysis is conducted to discuss the impacts of these parameters on the main results of the model.

(1) At present, China has not yet promulgated the 14th five-year plan. We set the economic growth rate of sectors for the two periods 2016-2020 and 2021-2025 according to the 13th five-year plan for socioeconomic development and the 13th five-year industrial plan of 31 regions. The total out of sectors directly affect the waste generation amount (see Eq. 10). Considering that the economic growth in the 14th five-year period may potentially differ from that in the 13th five-year period, such setting may bring uncertainties to the results. So we investigate the impacts of 5% increase in the growth rate of total output of the waste source sectors on the accumulative mitigation potentials of emissions. The detailed results are provided in **Table 9**.

(2) The waste structure in different regions are diverse across regions. According to the references, we consider the average values of the parameters in different regions and set that 45% of the MSW is CW suitable for incineration for power generation; 35% is FW available for biogas generation; 20% industrial wastewater is IOWW, among which 50% is suitable for biogas generation; 30% livestock manure is collectible from large breeding farms. Such assumptions are consistent for each region and may bring uncertainties to the results. Besides, with more

extensive and better implementation of waste sorting, the wastes can be collected from household will present an increment trend and the overall waste structure of a region will change potentially.

(3) The biogas generation coefficients (of FW, IOWW and BFM), power generation coefficients (of CW and biogas) and GHG and pollutant emission coefficients (of CW incineration and biogas power generation) for the WtE sectors listed in are referred to multiple references and determined as the corresponding average values. Along with improvement in WtE technologies, there would be better energy and environmental performances on these coefficients in terms of more biogas generation and power generation from unit waste, as well as smaller emissions from waste conversion. From this point of view, the predicted mitigation potentials of emissions may be conservative. While the GHG and pollutant emission intensity of sectors (emission of unit total output of sectors) are assumed to be constant, which would present a declining trend attributed to technological updating. From this point of view, the predicted mitigation potentials of emissions may be exaggerated. The above two aspects can offset mutually to some extent.

6. Conclusion

As a kind of bioenergy, urban wastes have a large potential for energy recovery. Due to China's large size and imbalanced development, various regions are with different levels of waste generation capacity, resulting in a need of more region-specific policies for waste management and energy-oriented waste utilization. In this study, four categories of urban wastes including CW, FW, IOWW and BFM are considered for energy recovery through corresponding WtE technologies. The PIO model with introduction of WtE sectors for each region is constructed. By developing a method system combining econometrics, CDM baseline method and the PIO model, the trends in waste generation, WtE potential and mitigation potentials for GHG and air pollutant emissions in 31 provincial regions of China from 2016 to 2025 are estimated. The research outcomes present different spatial distribution features of the energy and environmental benefits in 31 regions allowing appropriate policy recommendations to be proposed. Some main findings are as follows:

(1) By 2025, the largest amount of CW and FW available for energy recovery appears to Guangdong, reaching 115.05 Mt and 89.48 Mt, respectively. Hebei and Sichuan have the largest amount of IOWW (3724.89 Mt) and BFM (115.72 Mt), respectively.

(2) WtE power generation could amount to 11.8 billion kWh in Guangdong, followed by that in Jiangsu and Zhejiang. Among all regions, CW incineration power generation in 28 regions contributes to the largest proportion. Beijing has largest proportion of biogas power generation (3.85% in regional power generation structure).

(3) During 2016-2025, total accumulative mitigation potentials for GHG, SO_2, NO_x and SD emissions in Hebei are 577.57 Mt CO_2-e, 1.79 Mt, 0.89 Mt and 16.22 Mt, respectively, all of which are the largest across regions.

(4) In all regions, the sectors of PH, CM and OGE have larger mitigation potentials contributed by changes in industrial structure compared with other general sectors.

(5) Most regions with larger WtE potentials and mitigation potentials of emissions are in the East China (Guangdong, Jiangsu, Zhejiang, Hebei etc.) with higher level of population, household consumption and GDP. Less developed regions in the West China like Gansu, Qinghai, Ningxia etc. tend to have smaller potentials.

Due to different socioeconomic characteristics and waste resource potentials, different regions should consider their own realities and prescribe more appropriate waste management strategies for addressing local challenges of energy security and environmental concerns. Although this study is a case study for China, it has significant policy insights to other developing countries with similar conditions.

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