Environmental Pollution 404 (2026) 128447

Contents lists available at ScienceDirect

Environmental Pollution

journal homepage: www.elsevier.com/locate/envpol

Rural domestic waste generation characteristics and treatment-related greenhouse gas emissions: A case study of Guangdong Province, China

Yao He [a], Jie Zhang [a], Chen Lin [a], Linlin Xia [b,*], Yazhuo Wang [c,**], Hewen Zhou [d], Xun-an Ning [a]

[a] Guangdong Key Laboratory of Environmental Catalysis and Health Risk Control, Guangdong Engineering Technology Research Center of Solid Waste Resource Recovery and Harmless Treatment, School of Environmental Science and Engineering, Guangdong University of Technology, Guangzhou, 510006, China

[b] Guangdong Basic Research Center of Excellence for Ecological Security and Green Development, Key Laboratory for City Cluster Environmental Safety and Green Development of the Ministry of Education, School of Ecology, Environment and Resources, Guangdong University of Technology, Guangzhou, 510006, China

[c] Engineering Research Center for Clean Production of Textile Printing and Dyeing, Ministry of Education, Wuhan Textile University, Wuhan, 430073, China

[d] Institute of Thermal Science and Technology, Shandong University, Jinan, 250100, China

ARTICLE INFO

Keywords:
Rural domestic waste
Waste characteristics
Greenhouse gas emissions
Driving mechanism
Synergistic reduction

ABSTRACT

As China advances rural revitalization alongside its dual carbon goals, rural areas with lagging waste management are becoming new hotspots for solid waste and emissions growth, challenging coordinated pollution and carbon reduction. Yet, county-level data on rural domestic waste (RDW) generation and associated greenhouse gas (GHG) emissions remain scarce, leaving policy-making without granular empirical support. To bridge this gap, this study conducted the first systematic field survey across 30 underdeveloped counties in Guangdong, establishing a high-resolution inventory covering 4031.2 kt of RDW and 2005.8 kt CO_2e emissions. Food (45.4%) and plastics (17.0%) dominated the RDW stream, together contributing 96.5% of treatment-related emissions. Emission intensity followed a "low inland, high coastal" pattern, with coastal per capita emissions 30% higher, reflecting the cumulative emission effect due to inadequate local disposal capacity in rural areas after reduced urban spillover. Going beyond a descriptive inventory, we combine K-means clustering with spatial LMDI decomposition to identify drivers of inter-county emission variation. Population size was the primary driver, especially in mountainous counties experiencing population outflow. In more developed counties, technical factors such as treatment structure and intensity, played a stronger role, indicating emission reduction potential through technical optimization. Moving from single-pollutant to synergistic accounting, we further quantified the RDW-GHG co-reduction relationship, achieving a synergy coefficient of 0.94 through treatment optimization such as increased incineration. These findings offer a replicable county-level pathway for data-driven waste and carbon co-control in rural revitalization.

1. Introduction

The persistent intensification of the greenhouse effect poses significant challenges to natural ecosystems and human society. Global greenhouse gas (GHG) emissions recently reached a record 57.4 Gt of CO_2-equivalent (CO_2e), about 37 % higher than in 2000 (UNEP, 2023). China has pledged to peak carbon emissions by 2030 and achieve carbon neutrality by 2060 (Jia and Lin, 2021; Yang et al., 2021). This commitment places substantial pressure on the country to reduce GHG emissions, with solid waste management being a notable contributor (He et al., 2026a; He et al., 2026b; Kang et al., 2020). In 2016, solid waste management accounted for approximately 1.6 Gt CO_2e, representing about 5% of global GHG emissions (Kaza et al., 2018). Therefore, the implementation of effective waste management strategies is essential for national mitigation efforts (Cai et al., 2025; Huang et al., 2025).

The escalating accumulation of solid waste has emerged as a critical global challenge (Castell-Rüdenhausen, 2025; Chen et al., 2025a; Chen et al., 2025b; Lin et al., 2025). In China, governments at all levels have prioritized solid waste management, and a series of urban policies have achieved measurable emission reductions. For instance, Beijing reduced nearly 0.45 Mt CO_2e from waste management between 2011 and 2020 (Han et al., 2024). However, rural areas with relatively lagging disposal capabilities are gradually becoming new growth points for the waste

* Corresponding author.
** Corresponding author.
E-mail addresses: xialinlin@gdut.edu.cn (L. Xia), 2026008@wtu.edu.cn (Y. Wang).

https://doi.org/10.1016/j.envpol.2026.128447
Received 17 February 2026; Received in revised form 27 May 2026; Accepted 27 May 2026
Available online 27 May 2026

generation and emission discharge in the future. As the Rural Revitalization Strategy advances, rising living standards in rural communities have led to increased generation of rural domestic waste (RDW) and associated emissions, particularly in the southeastern coastal regions (Bian et al., 2022; Guan et al., 2015). Recognizing these challenges, national initiatives have increasingly targeted rural waste management. The 14th Five-Year Plan explicitly promotes the construction of county-level facilities for household waste sorting and disposal, and a Three-Year Action Plan has been launched to accelerate the establishment of a comprehensive rural waste management system. Nevertheless, RDW is scattered, and there are significant regional disparities in its production, making its characteristic data difficult to collect.

Accurate assessment of GHG emissions from the RDW sector is crucial for optimizing waste management strategies and supporting the achievement of China's carbon peaking and neutrality goals. This assessment fundamentally depends on understanding local waste generation characteristics, including quantities, compositions, and treatment methods. It is noteworthy that, similar to municipal solid waste, the generation characteristics of RDW display considerable regional variability. For example, rural communities in southwestern China report relatively low per capita RDW generation (0.18 kg/(capita·d)), with four main components—food waste, plastics, paper, and inert materials—accounting for nearly 82% of the total composition (Han et al., 2014). The Yellow River Delta region exhibited a much higher RDW generation of 0.56 kg/(capita·d), with food constituting about 88% of the total (Deng et al., 2022). Furthermore, the waste treatment practices also differ substantially, ranging from centralized landfilling and incineration in eastern and southwestern villages to open-site burial in many northwestern communities (Wang et al., 2017). These results reflect that RDW generation and treatment are highly heterogeneous, yet existing studies remain fragmented and often focused on the city-level resolution. To provide accurate data for policy-making and management, a higher resolution such as the county-level, for the generation of RDW and its associated GHG emissions is essential.

Data on waste generation characteristics can be collected through various methods, including field surveys, municipal records, and literature review. Previous studies on rural areas have mainly relied on single-method approaches to develop RDW inventories. Tian et al. (2018) calculated provincial RDW discharge according to survey data. Li et al. (2019) carried out field investigations and experiments to quantity RDW amounts and composition characteristics. By contrast, the integration of multiple investigative methods can enhance the accuracy of collected data, especially in underdeveloped rural areas where official documentation is often limited or unavailable (Han et al., 2019). Thus, this study overcomes limitations in single-method approaches by combining sampling techniques with literature-based research methods, aiming to provide more comprehensive datasets and reliable parameters for assessing GHG emissions in rural regions.

Currently, three main methodologies are commonly applied for carbon accounting in the waste sector: Life Cycle Assessment (LCA), Mass Balancing, and the Intergovernmental Panel on Climate Change (IPCC) method. LCA assesses the environmental impact of GHG emissions across the full life cycle of materials and energy inputs (Liu and Rajagopal, 2019), and Mass Balancing evaluates emissions by analyzing waste composition through energy balance equations (Fellner et al., 2007). The IPCC adopts a bottom-up approach to characterize regional GHG emissions in the waste sector. It has continuously refined and updated its methodology to incorporate the latest scientific and technological advancements, thereby enhancing the accuracy, effectiveness, and relevance of its emissions accounting framework. Recent studies have employed the IPCC method for time-series and spatial analysis. Li et al. (2017) investigated GHG emissions across 30 Chinese provinces, and found that resource-dependent regions had a higher potential for emission reductions. To further improve the accuracy of emission accounting, inventories have been extended from the provincial to the city level. Kang et al. (2022) compiled an inventory of GHG emissions from municipal solid waste for 294 China's prefecture-level cities. Han et al. (2024) developed an inventory for the municipal solid waste sector across 323 China's cities from 2011 to 2020 and conducted a comparative analysis across regions. Although these studies have made significant contributions to understanding GHG emissions in the waste sector, most of existing efforts have focused on the solid waste in economically developed cities, leaving less-developed rural counties underrepresented despite their growing waste generation and associated emissions.

The analysis of driving forces is significant for understanding the mechanisms underlying changes in GHG emissions from solid waste management and for formulating targeted mitigation policies. Among the available approaches, the Logarithmic Mean Divisia Index (LMDI) model is widely used to assess the driving factors of emission changes due to its advantages, including complete decomposition, absence of residual terms, and consistency between multiplicative and additive decomposition forms (Ang et al., 2015; Meng et al., 2019; Su and Ang, 2012). Kang et al. (2022) applied the model to conduct decomposition analysis across both temporal and spatial dimensions. Lu et al. (2020) demonstrated that urbanization level significantly influences GHG emissions from solid waste treatment, considering variations in urbanization levels among China's prefecture-level cities. Xiao et al. (2021), using Shanghai as a case study, identified five key temporal drivers of GHG emissions from solid waste treatment: economic development, population growth, emission intensity, power generation efficiency, and treatment structure. To date, however, few studies have examined the driving factors of GHG emissions from waste sector in rural areas. Furthermore, Furthermore, previous research on synergistic emission reduction has largely focused on GHGs (CO_2) and air pollutants such as SO_2 and PM (Gao et al., 2022; Zheng et al., 2024). While Chen et al. (2024) demonstrated that technological progress and structural adjustment are important channels for the co-reduction of CO_2 and various pollutants (including solid waste), the synergistic mechanism between CO_2 and solid waste alone remains insignificant. Notably, the synergy between GHG emissions and solid waste, particularly RDW, has rarely been studied. Consequently, the synergistic effects between RDW and GHG remain unclear, and the driving factors for GHG of RDW disposal in Guangdong counties need to be further identified.

To address the critical data gap in underdeveloped rural regions, this study focuses on 30 counties with lagging waste disposal capability in the less-developed eastern, western, and northern regions of Guangdong Province, a major economic hub along China's southeastern coast. We conducted extensive field surveys and sampling, distributing 450 structured questionnaires to local governments, landfills, and incineration plants (with 438 valid responses), and analyzed RDW composition following national standards (Zhuang et al., 2008). By integrating this unique first-hand data with literature-based investigations, we developed one of the first comprehensive county-level inventories of both RDW generation and its treatment-related GHG emissions in Guangdong Province. Methodologically, this study introduces a novel integration of three analytical approaches to the rural waste context. First, K-means clustering was used to delineate regional characteristics based on socio-economic heterogeneity rather than arbitrary administrative boundaries. Second, a spatial LMDI decomposition model was applied to quantify the key drivers of inter-county emission variations. Third, a synergy analysis was conducted to assess the co-reduction potential between RDW generation and GHG mitigation, an application rarely attempted in the rural waste sector. Our results provide a micro-level empirical foundation for improving rural waste management. By quantifying GHG emissions, clarifying the underlying drivers of regional differences, and revealing the synergistic nexus between RDW generation and emissions, this study offers actionable insights for targeted policy interventions. Ultimately, it fills a critical data gap in rural areas and supports the integration of pollution control and carbon reduction in China's rural revitalization strategy.

2. Data and methods

2.1. RDW generation survey implementation

2.1.1. Investigated area description

Guangdong is one of China's most economically advanced provinces, yet it faces notable regional disparities, with the areas outside the Pearl River Delta, particularly in the eastern, western, and northern parts, remaining relatively underdeveloped. These less-developed regions encompass rural areas across 30 counties in 11 cities (Fig. 1). According to the "13th Five-Year Plan" for RDW treatment in Guangdong Province and relevant database, the average treatment rate of domestic waste, including RDW, across these counties has exceeded 99% since 2018 (CEIC, 2024). Given this negligible untreated fraction, in this study, the quantity of RDW generated is assumed to be equal to the quantity of RDW disposed.

2.1.2. Survey content

To determine the total quantity and treatment distribution of RDW, structured questionnaire surveys were conducted with key entities in the waste disposal sector. A total of 450 questionnaires were distributed across all 30 counties (15 per county) to ensure spatial coverage. Respondents included personnel from local Housing and Urban-Rural Development Bureaus, landfill sites, incineration plants, and the composting facilities in Xinxing County. The 12 invalid questionnaires were excluded due to incomplete key sections or logical inconsistencies. The final valid sample (n = 438) achieved a response rate of 97.3%, and the distribution of valid responses across counties was proportional to the number of waste treatment facilities in each county, ensuring representativeness of the treatment structure data.

To determine RDW composition, field sampling was carried out following the Chinese national standard CJ/T313-2009 (Zhuang et al., 2008). In each selected county, five representative townships were chosen based on economic development level, yielding 15 sampling points per county per sampling round. Sampling was conducted quarterly (March, June, September, and December) to capture seasonal variations. At each sampling point, waste was collected and sorted over three consecutive days per sampling round to account for intra-week variability. Sample screening criteria excluded (i) waste from special events and (ii) samples with visible contamination from non-domestic sources. Quality control procedures included (i) standardized training for all field investigators, (ii) double-weighting of 10% of randomly selected samples for cross-checking, (iii) inter-rater reliability checks for waste classification, and (iv) use of standardized sampling tools across all sites to ensure methodological consistency. The proportion of each component P_i was then calculated as:

$$P_i = \frac{M_i}{M} \qquad \text{Eq. (1)}$$

where P_i is the proportion of RDW composition i (%); M_i is the wet weight of RDW composition i (kg); M is the total wet weight of the RDW sample (kg).

2.2. Calculation of GHG emissions from RDW treatments

The treatment-related GHG emissions were estimated by IPCC method based on the data of RDW treatment activity (landfill, incineration and compost), and IPCC default and literature reported values of emission factors (Cai et al., 2018; Lou et al., 2017; Zhou et al., 2014). The emissions primarily consist of CH_4, CO_2 and N_2O. Among them, CH_4 is the most significant non-CO_2 greenhouse gas, with a global warming potential up to 28 times greater than that of CO_2, and waste landfills constitute its third-largest emission source (Cai et al., 2018). N_2O has the global warming potential 265 times that of CO_2 (IPCC, 2014). In this study, the county-level GHG emissions from RDW treatments are ultimately expressed as the sum of CO_2-equivalent emissions.

2.2.1. RDW landfill

The GHG emission from RDW landfill is calculated according the following equation.

$$L_{CH_4} = \sum_{i=1}^{4} M_l \times P_i \times C \times D_i \times D_f \times F \times \frac{16}{12} \times (1 - R) \times (1 - O) \qquad \text{Eq. (2)}$$

i ∈ food waste, paper, cloth and wood

Where L_{CH4} denotes the GHG emissions (CH_4) resulting from the disposal of RDW in landfills; M_l denotes the mass of waste undergoing landfill treatment; P_i represents the proportion of degradable RDW of type i; C is the correction factor for CH_4; D_i represents the degradable organic carbon content associated with RDW type i; D_f represents the fraction of degradable organic carbon that is actually decomposed; F represents the CH_4 fraction in the landfill gas; R is the recovery rate for CH_4; O represents the CH_4 oxidation factor. C, D_f, F, R, and O all adopt IPCC recommended default values of 0.92, 0.5, 0.5, 0.24, and 0.1, respectively. The value of D_i for each composition is shown in Table 1.

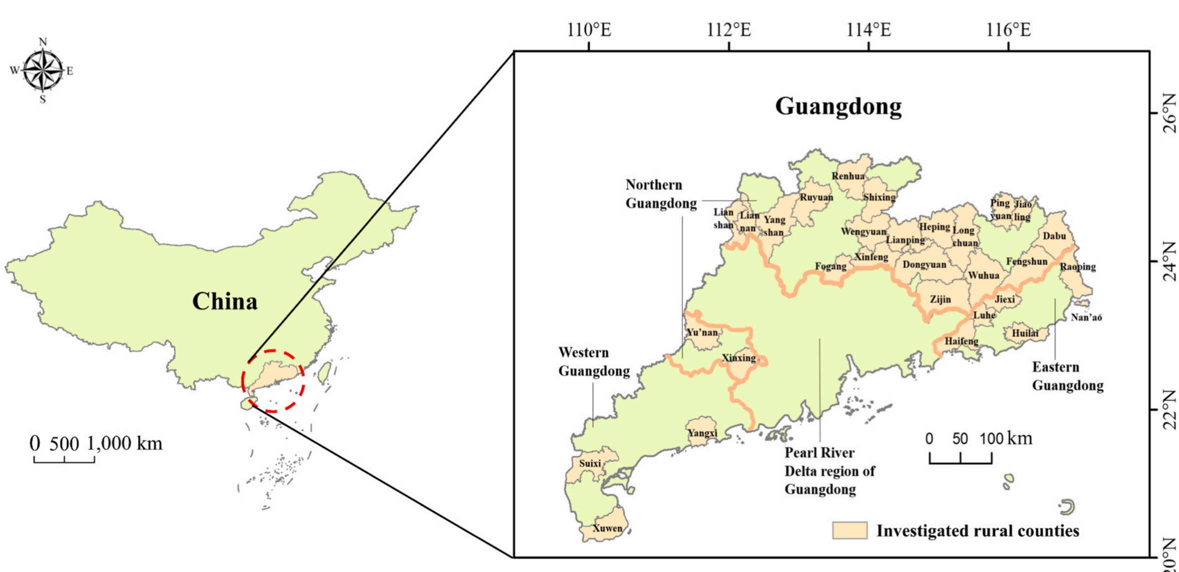

Fig. 1. Spatial distribution of the investigated counties in Guangdong Province.

Table 1
Three types of carbon content in solid waste compositions (Cai et al., 2018; Kang et al., 2022; Zhao et al., 2019).

	Food waste	Paper	Cloth	Wood	Plastic
Degradable organic carbon content (D_i)	0.11	0.24	0.27	0.33	0
Carbon content (CC_i)	0.5	0.46	0.5	0.5	0.75
Mineral carbon content (FC_i)	0.01	0.01	0.5	0.01	1

2.2.2. RDW incineration

The GHG emission from RDW incineration is calculated according to Eq. (3).

$$I_{CO_2} = \sum_{i=1}^{5} M_{inc} \times P_i \times CC_i \times FC_i \times E \times \frac{44}{12} \quad \text{Eq. (3)}$$

i ∈ food waste, paper, cloth, wood and plastic

Where I_{CO2} represents the GHG emissions (CO_2) resulting from incineration; M_{inc} represents the volume of incineration treatment; P_i represents the proportion of RDW type i; CC_i represents the carbon content of type i; FC_i represents the mineral carbon content of type i; E refers to the incineration efficiency, with a default value of 0.95. Carbon and mineral carbon contents of the five compositions of RDW are shown in Table 1. CH_4 and N_2O emissions from RDW incineration are calculated by using the default values of 6.5 kg/t and 0.06 kg/t, respectively.

2.2.3. RDW compost

The GHG emission from RDW compost is calculated according Eqs. (4) and (5).

$$C_{CH_4} = M_C \times EF_C \quad \text{Eq. (4)}$$

$$C_{N_2O} = M_C \times EF_N \quad \text{Eq. (5)}$$

where C_{CH4} and C_{N2O} refer to the GHG emissions (CH_4 and N_2O) from compost; M_C represents compost treatment quantity; EF_C is the CH_4 emission factor of compost, with a default value of 4 kg/t; EF_N denotes the N_2O emission factor of compost, with a default value of 0.3 kg/t.

2.2.4. Sensitivity analysis

To assess the robustness of our GHG emission estimates to the choice of emission factors, a one-factor-at-a-time sensitivity analysis was conducted. Key emission factors (e.g., degradable organic carbon content D_i, methane correction factor C, methane recovery rate R, incineration efficiency E, compost emission factors EF_C and EF_N) were varied by ±10% from its default value, while holding all other factors constant. The percentage change in total GHG emissions was calculated to identify the most influential parameters. This ±10% variation was selected based on typical uncertainty ranges reported in similar waste-sector GHG studies (van Middelaar et al., 2012).

2.3. K-means clustering

K-means clustering is a widely used and computationally efficient algorithm for partitioning data into distinct groups, owing to its conceptual simplicity. The algorithm requires the number of clusters (k) to be specified in advance and iteratively assigns data points to the nearest cluster centroid based on a predefined distance metric. Traditional geographical classification approaches often face significant limitations when characterizing the spatial heterogeneity of RDW generation and the GHG emissions from treatment processes. To address these limitations, this study applies the K-means clustering method to group the investigated counties in Guangdong Province according to GDP, population and RDW generation levels, enabling a more nuanced analysis of the spatial distribution patterns.

2.4. Spatial LMDI decomposition of treatment-related GHG emissions

The Kaya identity enables the quantification of carbon emissions by establishing a linkage between carbon footprints and driving factors such as population and economic activity. Given the substantial regional disparities across the studied counties, this study extends the original Kaya identity by incorporating additional variables including urbanization level, into the analytical framework, and constructs an LMDI decomposition model to examine the drivers of GHG emissions from RDW treatment (Xiao et al.), thereby offering insights into the mechanisms underlying inter-county emission variations.

This study applies a spatial adaptation of the LMDI decomposition method, which fixes the time dimension and compares each county's emissions against the provincial average (Kang et al., 2022). The decomposition is expressed as follows:

$$\begin{aligned} GHG &= \sum_{j=1}^{3} \frac{GHG}{D_j} \times \frac{D_j}{D} \times \frac{D}{GDP} \times \frac{GDP}{UP} \times \frac{UP}{PS} \times PS \\ &= \sum_{j=1}^{3} EI_j \times TS_j \times TI \times EO \times UL \times PS \end{aligned} \quad \text{Eq. (6)}$$

where the six driving factors are: emission intensity (*EI*), RDW treatment structure (*TS*), RDW treatment intensity (*TI*), economic output (*EO*), urbanization level (*UL*), and population size (*PS*). Here, subscript j denotes one of the three RDW treatment methods (landfill, incineration, and compost); D_j is the RDW treatment volume for method j; D is the total RDW treatment amount; *GDP* is the annual gross domestic product of a county; *UP* is the urban population of a county; and *PS* is the total population size. *EI*, *EO*, and *PS* are standard components in Kaya-type decompositions of waste-sector emissions (Han et al., 2024; Kang et al., 2022). The remaining three factors, *UL*, *TS*, and *TI*, are specifically adapted to the rural Guangdong context for the following reasons. First, *UL* is explicitly included because rural counties in Guangdong experience substantial population outflows and varying degrees of urban integration, which directly affect waste generation patterns and collection efficiency; Second, *TS* and *TI* capture the technical heterogeneity across counties, as landfill still dominates in less-developed mountainous areas while incineration is expanding in coastal industrial counties, a technical divide less pronounced in urban waste management studies.

To quantify the contribution of each factor to the spatial emission gap, the additive decomposition is defined as follows (Kang et al., 2022):

$$\Delta GHG = GHG^T - GHG^B = \Delta EI + \Delta TS + \Delta TI + \Delta EO + \Delta UL + \Delta PS \quad \text{Eq. (7)}$$

where superscript T denotes the target county, and superscript B denotes the provincial average baseline. Thus, ΔGHG represents the difference in GHG emissions between a specific county and the provincial benchmark. The LMDI method is mathematically path-independent and has been widely applied in spatial decomposition analyses (Han et al., 2024). The contribution of each factor is then calculated using equations (8)–(13), according to Kang's work (Kang et al., 2022). The detailed explanations for these factors are shown in Table 2.

$$\Delta EI = \frac{GHG^{T1} - GHG^{B1}}{\ln GHG^{T1} - \ln GHG^{B1}} \times \ln \frac{\frac{GHG^{T1}}{D^{T1}}}{\frac{GHG^{B1}}{D^{B1}}} + \frac{GHG^{T2} - GHG^{B2}}{\ln GHG^{T2} - \ln GHG^{B2}} \times \ln \frac{\frac{GHG^{T2}}{D^{T2}}}{\frac{GHG^{B2}}{D^{B2}}} \quad \text{Eq. (8)}$$

$$\Delta TS = \frac{GHG^{T1} - GHG^{B1}}{\ln GHG^{T1} - \ln GHG^{B1}} \times \ln \frac{\frac{D^{T1}}{D^{T}}}{\frac{D^{B1}}{D^{B}}} + \frac{GHG^{T2} - GHG^{B2}}{\ln GHG^{T2} - \ln GHG^{B2}} \times \ln \frac{\frac{D^{T2}}{D^{T}}}{\frac{D^{B2}}{D^{B}}} \quad \text{Eq. (9)}$$

Table 2
Definitions of driving factors.

Factors	Definitions
ΔEI	Emission intensity effect, revealing changes in GHG emissions from RDW treatment, resulting from variations in the quantity of GHGs emitted per unit of RDW processed
ΔTS	Treatment structure effect, revealing variations in GHG emissions from RDW treatment resulting from the influence of different RDW treatment methods
ΔTI	Treatment intensity effect, revealing changes in GHG emissions from RDW treatment resulting from variations in the amount of RDW treatment per unit of GDP
ΔEO	Economic output effect, revealing changes in GHG emissions from RDW treatment driven by per capita GDP growth
ΔUL	Urbanization level effect, revealing changes in GHG emissions from RDW treatment attributable to variations in urbanization levels
ΔPS	Population size effect, revealing changes in GHG emissions from RDW treatment resulting from the variations in population size

$$\Delta TI = \frac{GHG^{T1} - GHG^{B1}}{\ln GHG^{T1} - \ln GHG^{B1}} \times \ln \frac{\frac{D^T}{GDP^T}}{\frac{D^B}{GDP^B}} + \frac{GHG^{T2} - GHG^{B2}}{\ln GHG^{T2} - \ln GHG^{B2}} \times \ln \frac{\frac{D^T}{GDP^T}}{\frac{D^B}{GDP^B}} \tag{Eq. (10)}$$

$$\Delta EO = \frac{GHG^{T1} - GHG^{B1}}{\ln GHG^{T1} - \ln GHG^{B1}} \times \ln \frac{\frac{GDP^T}{UP^T}}{\frac{GDP^B}{UP^B}} + \frac{GHG^{T2} - GHG^{B2}}{\ln GHG^{T2} - \ln GHG^{B2}} \times \ln \frac{\frac{GDP^T}{UP^T}}{\frac{GDP^B}{UP^B}} \tag{Eq. (11)}$$

$$\Delta UL = \frac{GHG^{T1} - GHG^{B1}}{\ln GHG^{T1} - \ln GHG^{B1}} \times \ln \frac{\frac{UP^T}{PS^T}}{\frac{UP^B}{PS^B}} + \frac{GHG^{T2} - GHG^{B2}}{\ln GHG^{T2} - \ln GHG^{B2}} \times \ln \frac{\frac{UP^T}{PS^T}}{\frac{UP^B}{PS^B}} \tag{Eq. (12)}$$

$$\Delta PS = \frac{GHG^{T1} - GHG^{B1}}{\ln GHG^{T1} - \ln GHG^{B1}} \times \ln \frac{PS^T}{PS^B} + \frac{GHG^{T2} - GHG^{B2}}{\ln GHG^{T2} - \ln GHG^{B2}} \times \ln \frac{PS^T}{PS^B} \tag{Eq. (13)}$$

where superscript T_1 and B_1 respectively denote the values of the target county and the provincial average under landfill treatment; T_2 and B_2 respectively represent the values of the target county and the provincial average under incineration treatment.

Regarding statistical testing, the reliability of decomposition results is derived from three cross-validating approaches. (i) The sum of the six decomposed effects equals the total emission difference between each county and the provincial average, with a negligible rounding residual, confirming numerical accuracy. (ii) LMDI is independent of decomposition order, which eliminates order-induced bias. (iii) The direction and relative magnitude of the decomposed factors are compared with known local contexts and with findings from previous waste-sector decomposition studies in other Chinese regions to verify the rationality of results.

2.5. Synergy degree analysis

This study adopts the emissions reduction cross-elasticity index proposed by Mao (Mao et al., 2012) to analyze the synergistic reduction degree of RDW generation and its treatment-related emission. The specific formula is as follows.

$$Els_{g/w} = \frac{\frac{\Delta G}{G_0}}{\frac{\Delta W}{W_0}} \tag{Eq. (14)}$$

where $Els_{g/w}$ stands for the emissions reduction cross-elasticity index. ΔG and ΔW represent the reduction in GHG and RDW in the current year (2023) compared to the previous year (2022), respectively. G_0 means the emission of GHG for the current year. W_0 means the emission of RDW for the current year. According to the method proposed by Gao et al. (2022), the synergy degree of emission reduction is assigned and expressed as the synergy degree of emission reduction between RDW generation and its treatment related GHG emissions. The definitions of the synergy degree for emission reductions are summarized in Table 3.

2.6. Data sources

Information on RDW generation and its treatment methods was primarily obtained from field surveys (Section 2.1) and supplemented by literature reviews of documented reports issued by local county governments during 2022-2023. RDW composition data were collected through field sampling as described in Section 2.1. The socio-economic data including GDP and population data was acquired from National Economic and social development statistical Bulletin of each county and Guangdong Statistical Yearbooks.

3. Characteristics of RDW generation and associated GHG emission

3.1. Regional delineation

In this study, GDP, POP and RDW generation are chosen as indicators for regional delineation using of K-means clustering analysis (Fig. 2). Detailed data for the investigated counties are presented in Table S1. The C1 cluster contributes only 24.1% of the total RDW generation, with an average of 74.8 kt, significantly lower than that of the other two clusters. In contrast, the C3 cluster includes the fewest counties, yet contributes 29.7% of the total RDW generation, with the highest average generation of 199.4 kt. Moreover, the C2 cluster includes the largest number of counties and accounts for 46.2% of the total generation, which represents the highest proportion among the clusters. As shown in Fig. 2a, RDW generation tends to be higher in the counties with larger populations and higher GDP, suggesting a positive correlation between RDW generation and both GDP and population size. Fig. 2b illustrates the distribution of counties at different RDW generation levels in each cluster. The counties in C1 exhibit a gourd-like distribution pattern, and most of them have a low RDW generation level (<100 kt). While, the counties in C2 and C3 display broader spatial distributions. Specifically, the counties in C2 are concentrated in two distinct zones, centered around RDW generation levels of 100 kt and 220 kt, respectively, whereas the counties in C3 are centered at 170 kt.

3.2. RDW generation characteristics

Fig. 3 illustrates distribution of RDW generated in Guangdong Province by geographic region, composition, and treatment methods, and compares the amount across the investigated counties in different clusters with respect to composition and disposal method. The total amount of RDW produced in the 30 counties is 4031.2 kt. As shown in Fig. 3a, the amount of RDW generated follows the order of northern (2367.0 kt) > eastern (1047.9 kt) > western (616.3 kt), since the number of counties in western (3 counties) and eastern Guangdong (6 counties) is significantly lower than that in northern region (21 counties). Conversely, the average amount of RDW generated per county in the relatively economically developed western and eastern regions of Guangdong is 205.3 and 174.4 kt, respectively, which are much higher

Table 3
Definition of synergy degree for emission reductions.

Type	Satisfied condition
Anti-synergy	$Els_{g/w} > 0, \frac{\Delta G}{G_0} < 0, \frac{\Delta W}{W_0} < 0$
Positive-synergy	$Els_{g/w} > 0, \frac{\Delta G}{G_0} > 0, \frac{\Delta W}{W_0} > 0$
Non-synergy (GHG increase and RDW decrease)	$Els_{g/w} \leq 0, \frac{\Delta G}{G_0} < 0, \frac{\Delta W}{W_0} > 0$
Non-synergy (GHG decrease and RDW increase)	$Els_{g/w} \leq 0, \frac{\Delta G}{G_0} > 0, \frac{\Delta W}{W_0} < 0$

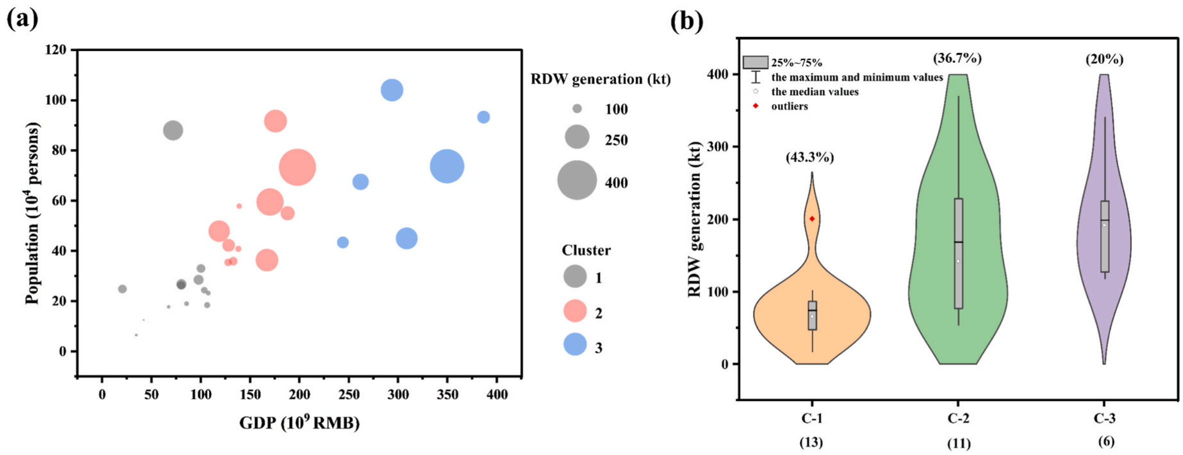

Fig. 2. (a) K-means clustering results based on GDP, population and RDW generation, and (b) distribution of counties in each cluster (the size of the dots indicates RDW generation amount, and the colors represent different clusters). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

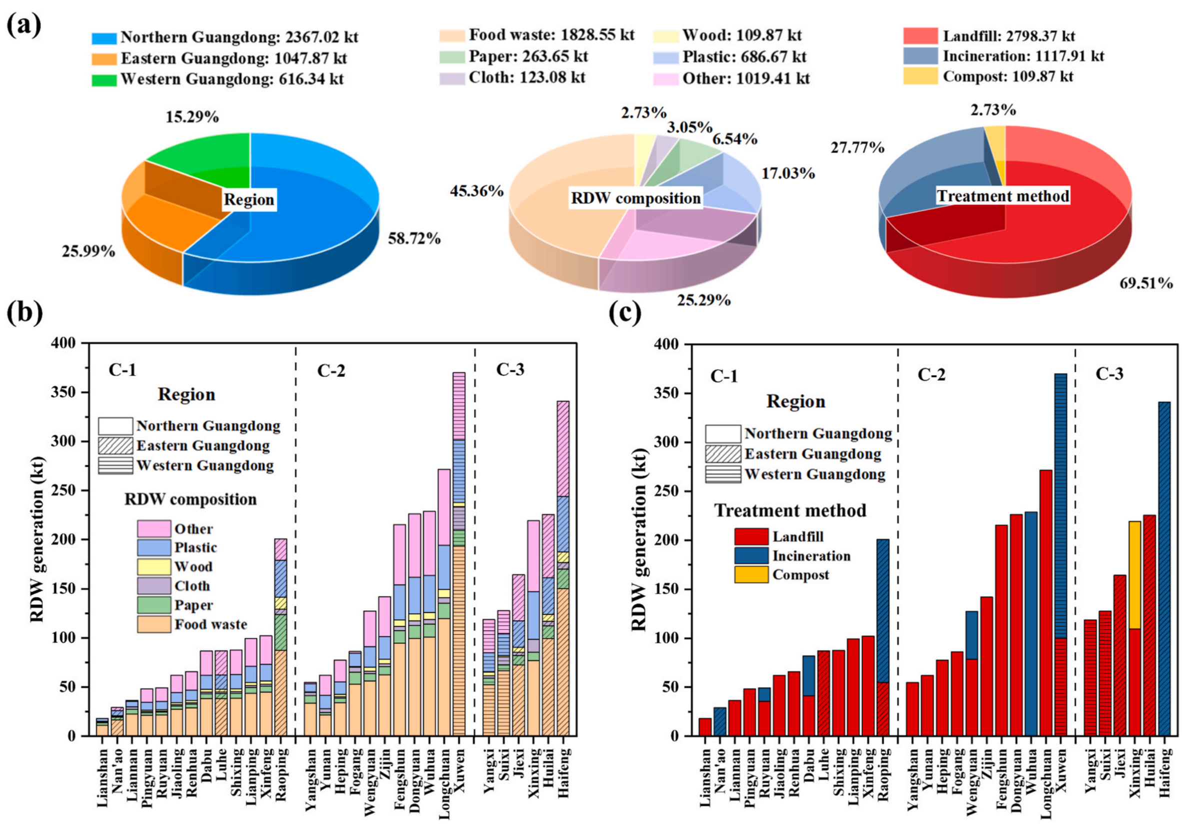

Fig. 3. (a) Proportions of RDW generation in the investigated rural areas of Guangdong Province by geography, composition, and treatment methods. Comparisons of (b) yield of each composition and (c) amount of each treatment method across the counties in different clusters.

than in the north (112.7 kt). It demonstrates a fact that economic development is the most significant factor influencing the generation of solid waste whether in urban or rural areas (Cui and Wei, 2024). The waste mainly consists of food waste, plastic, paper, cloth, and wood with total generations of 1828.6, 686.7, 263.7, 123.1, and 109.9 kt, respectively, where food waste and plastic occupy the largest compositions, accounting for 45.4% and 17.0%. According to the Engel's law, lower household wealth levels correspond to a higher proportion of food consumption expenditure in total consumption. Thus, the large generation of food waste in the rural counties of Guangdong is due to their lower level of economic development. In contrast, the major components of solid waste in the developed area such as Guangzhou city in the Pearl River Delta of Guangdong are plastic and cloth (up to 46.0%) (Zhou et al., 2014).

As indicated in Fig. 3b, the counties with the highest food waste generation of Cl, C2 and C3 are Raoping, Xuwen, and Haifeng, with 87.5, 193.4, 150.3 kt, respectively. Apart from their economic development levels, the phenomenon can be due to their coastal locations, giving rise to thriving fishing industry and high seafood consumption. Following food waste, plastic generation ranks as the second largest composition of RDW. Plastic generation is relatively high across counties in eastern Guangdong, such as Raoping and Haifeng, reporting particularly high generation of 37.5 and 56.3 kt, respectively, attributed to the significant presence of the plastic industry in these areas. Besides, the volumes of paper, cloth, and wood waste are at relatively low levels for all the investigated counties. It is noted that the wood waste amounts in Yunan and Xinxing approach zero, which should be linked to the stringent forest protection policy implemented by their local governments.

Fig. 3c shows that landfill remains the predominant disposal method for RDW in rural Guangdong, accounting for 69.5% of the total disposal amount. This proportion is notably lower than the national rural average of 80% (Bian et al., 2022), reflecting Guangdong's relatively advanced economic development and greater incineration capacity. Incineration is used in 8 counties, while composting is adopted only in Xinxing County. The distribution of treatment methods varies significantly across regions, with eastern coastal regions reporting higher incineration amount (516.3 kt) than northern inland regions (331.6 kt). This discrepancy closely aligns with the unequal levels of socio-economic development observed throughout Guangdong. Consequently, a half of the counties in eastern Guangdong utilize incineration as a method of RDW treatment due to their prosperous economy and limited land resources. In contrast, only 4 out of the 21 counties in the underdeveloped northern region with large area opt for incineration treatment. Additionally, as the increase of waste generation, the counties are more inclined to utilize incineration treatment. For example, the waste generated in Raoping, Xuwen, and Haifeng are the highest among C1, C2, and C3, and they all adopt incineration as the predominant method. In summary, socio-economic and geographical factors shape RDW composition and disposal in rural Guangdong, with food waste being the largest component and landfill the main method. The more developed eastern region, which produces more waste, is increasingly adopting incineration.

3.3. Inventory of GHG emissions from RDW treatments

Considering that there is a strong relationship between GHG emission and RDW generation, we followed the same K-means clustering analysis method with RDW generation in Section 3.1, and the clustering results of GHG emission are presented in Fig. S1 and Table S2. The patterns of GHG emissions from RDW treatments within each cluster are similar to those of its generation. Consequently, the correlation between GDP/POP and GHG emissions obeys the same trend as with RDW generation (Fig. S1a). Fig. S1b illustrates the distribution of GHG emissions for the 30 counties. The data distributions of C1 and C3 GHG emissions closely match those of RDW generation, while C2 GHG emissions concentrate around 70 kt CO_2e, unlike C2 waste generation, which shows two distinct levels.

Fig. 4a shows that overall GHG emissions exhibit a spatial distribution pattern of higher levels in the coastal region, where most of them exceed the average of the investigated counties, which is 120 kt CO_2e. The total GHG emissions from RDW of the 30 counties is 2005.8 kt CO_2e, with the eastern, western, and northern regions accounting for 572.5, 329.5, and 1103.8 kt CO_2e, respectively (Fig. S2). In terms of the compositional contribution, food waste, plastic, paper, cloth, and wood generate 1454.7, 491.7, 18.3, 25.1, and 6.9 kt CO_2e, respectively (Fig. 4b). Obviously, the predominant composition of RDW, food waste, is also the major source of GHG emissions, accounting for up to 72.1%, in contrast to the lower contributions of plastic, paper, cloth, and wood waste, which are 24.4%, 0.9%, 1.2%, and 0.3%, respectively.

When correlating the data in Fig. 4c with the previously mentioned results, it can be observed that in counties without incineration facilities, plastic shows zero GHG emissions. This suggests that plastic underwent minimal degradation in landfills over a short period, thereby releasing fewer GHGs. For instance, Xinxing County, which mainly adopts landfill and composting methods, has the third highest waste generation among C3 counties, but its GHG emissions are comparable to the lowest

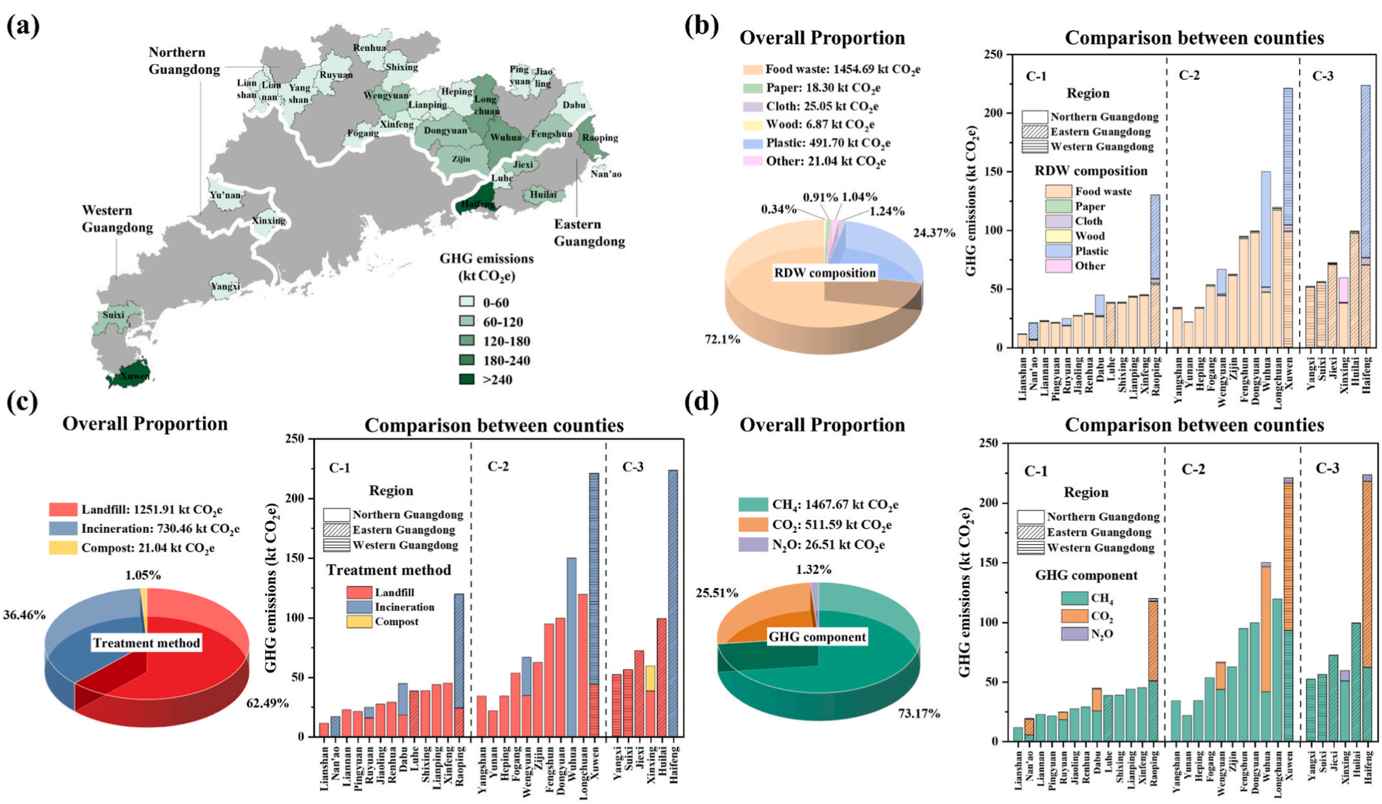

Fig. 4. (a) Distribution of county-level GHG emissions from RDW treatment in rural Guangdong. Comparisons of overall and county-level GHG emissions by RDW (b) compositions, (c) treatment methods, and (d) greenhouse gas components.

emissions within its cluster. Composting-related emissions are negligible at the provincial level, appearing only in Xinxing County. Therefore, the amount of GHG emissions is associated not only with the quantity and composition of waste but also closely related to its disposal method. In contrast, in counties with incineration plants, plastic waste becomes a major GHG source. In Nan'ao and Wuhua counties, plastic constitutes only 18.4% and 16.5% of RDW, respectively, yet its GHG emissions account for the majority of the total in both counties. Similar results were also reported by Kwon et al. (2023) who found that plastic waste consisted of 25% of solid waste in Seoul city, South Korea, but the GHG emissions were up to 92% of the total. This phenomenon can be ascribed to the fact that plastics have significantly higher C_{ci} (carbon content fraction) and F_{ci} (fossil content) compared to other solid wastes, which leads to greater GHG emissions during incineration treatment. From the pie chart in Fig. 4c, it can be also found that landfill was the primary method for waste disposal in the rural area of Guangdong. However, the proportion of waste incineration treatment has been notably increasing recently, and over time, plastics will become the primary source of GHG emissions (Bian et al., 2022). Consequently, strengthening plastic recycling should be a policy priority. Furthermore, in the 30 counties where landfill is dominant, the decomposition of paper, cloth, and wood waste is slow. Over a long period, most of the carbon in these materials remains stably sealed in solid form within the landfill and is not converted into GHG emissions. Therefore, despite the considerable quantities of paper, cloth, and wood waste (Fig. 3b), their GHG emission intensity under landfill disposal remains very low (Fig. 4b).

Fig. 4d clearly demonstrates that CH_4 stands as the primary greenhouse gas among the 30 counties, accounting for 73.2% of the total GHG emission amount (1467.7 kt CO_2e). CH_4 is the main product emitted from landfill treatment, with a global warming potential (GWP) more than 28 times higher than that of CO_2. Consequently, landfill is likely to exert a stronger influence on global warming compared to incineration. Moreover, incineration produces CO_2 and N_2O. Nevertheless, the total emission of N_2O (26.5 kt CO_2e) is significantly lower than that of CO_2 (511.6 kt CO_2e), which can be ascribed to the fact that N_2O is solely generated from a small fraction of emissions from incineration and compost. In conclusion, GHG emissions of RDW in Guangdong are affected by the quantity and composition of waste as well as its disposal method. Although landfill might lead to fewer GHG emissions for non-degradable waste like plastics, incineration aids in reducing the release of CH_4, which has an extremely high GWP impact.

3.4. GHG emission characteristics for different counties

Fig. 5a and b shows the county-level GHG emission intensities from RDW treatment in rural Guangdong. The spatial distributions of GHG emissions per unit of GDP and per capita largely align with that of total emissions, with elevated intensities concentrated in the eastern and western coastal regions. This “low inland, high coastal” emission pattern reflects intertwined institutional, economic, and management mechanisms. Institutionally, coastal counties have benefited from stronger policy enforcement under the Rural Revitalization Strategy, accelerating incineration adoption, which reduces CH_4 but increases CO_2 from plastics. Economically, higher GDP per capita and land scarcity in coastal areas drive incineration investment, while higher consumption of packaged goods increases plastic waste share which is a key source of incineration-related CO_2 emissions. In contrast, inland counties with lower fiscal capacity and abundant land retain low-cost landfilling. From a management perspective, coastal counties implement incineration-oriented treatment, under which waste is fully combusted, releasing its embedded carbon as CO_2. However, inland counties rely predominantly on landfilling, where waste degrades slowly and generates minimal short-term GHG emissions. These three mechanisms jointly explain why coastal per capita emissions are 30% higher than inland.

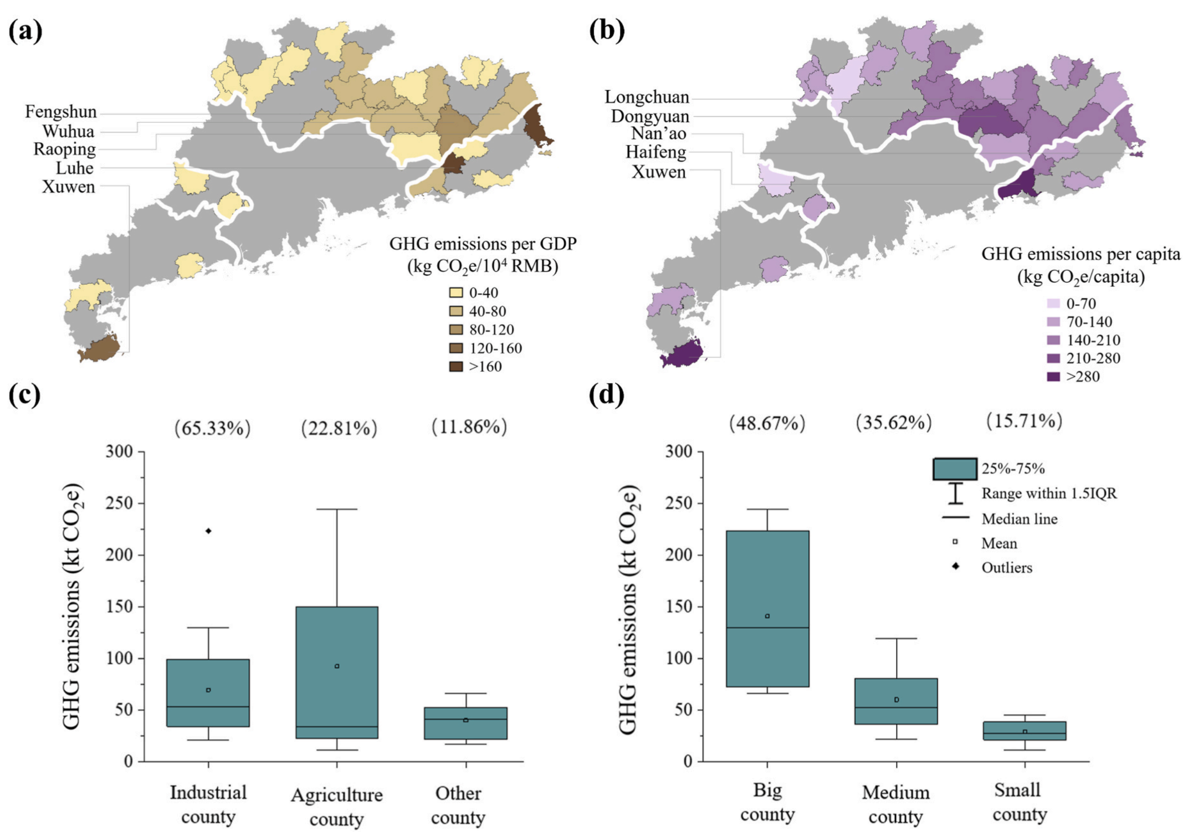

Fig. 5. County-level GHG emissions intensity: (a) per GDP and (b) per capita. Emission characteristics of different types of counties divided by (c) industrial structure and (d) population.

Average emission intensities in coastal areas reached 78.0 kg $CO_2e/10^4$ RMB and 177.0 kg CO_2e/capita, significantly exceeding inland values of 40.7 kg $CO_2e/10^4$ RMB and 136.1 kg CO_2e/capita, reflecting the higher emissions relative to economic output and population size in these regions. Specifically, the three counties with the highest GHG emissions per unit of GDP, such as Luhe, Raoping, and Xuwen (intensity >120 kg $CO_2e/10^4$ RMB), are largely medium-to large-scale industrial counties in the relatively developed eastern coastal zone. In contrast, counties with low emission intensities per unit of GDP, such as Ruyuan, Yangxi, Yunan, and Xinxing (intensity <25 kg $CO_2e/10^4$ RMB), are predominantly located in less-developed northern inland areas. Moreover, the highest per capita emissions (>300 kg CO_2e/capita) were observed in the coastal counties of Xuwen (west) and Haifeng (east).

Based on the GDP structure and population of each county, counties are classified into different types (Fig. 5c and d). Fig. 5c reveals remarkable variations in GHG emissions among counties with diverse GDP structures. Industrial counties exhibit the highest contribution of 65.3% to emissions, with values predominantly ranging from 35 to 100 kt CO_2e and a median of approximately 50 kt CO_2e. In contrast, agricultural counties demonstrate relatively lower emission contributions. The emission amounts are distributed between 20 and 150 kt CO_2e, and the median is around 30 kt CO_2e. These findings imply a positive correlation between the level of industrialization and the magnitude of GHG emissions from RDW treatment. Guan et al. (2017) previously indicated that domestic waste tends to contain a higher proportion of high-carbon materials (e.g., plastics) in highly industrialized regions, which leads to higher treatment-related GHG emissions. It can also be observed that the emission amounts of agricultural counties are the most dispersed, probably because of the significant disparity in population size. In addition, big counties with larger populations have higher median of GHG emissions from RDW (Fig. 5d). The median emission of big counties is 130.6 kt CO_2e, which is much higher than that of medium counties (52.8 kt CO_2e) and small counties (27.6 kt CO_2e). Specifically, 7 big counties, which account for 23.3% of the total number of investigated counties, contribute to 48.7% of the total emissions, illustrating the substantial influence of population size.

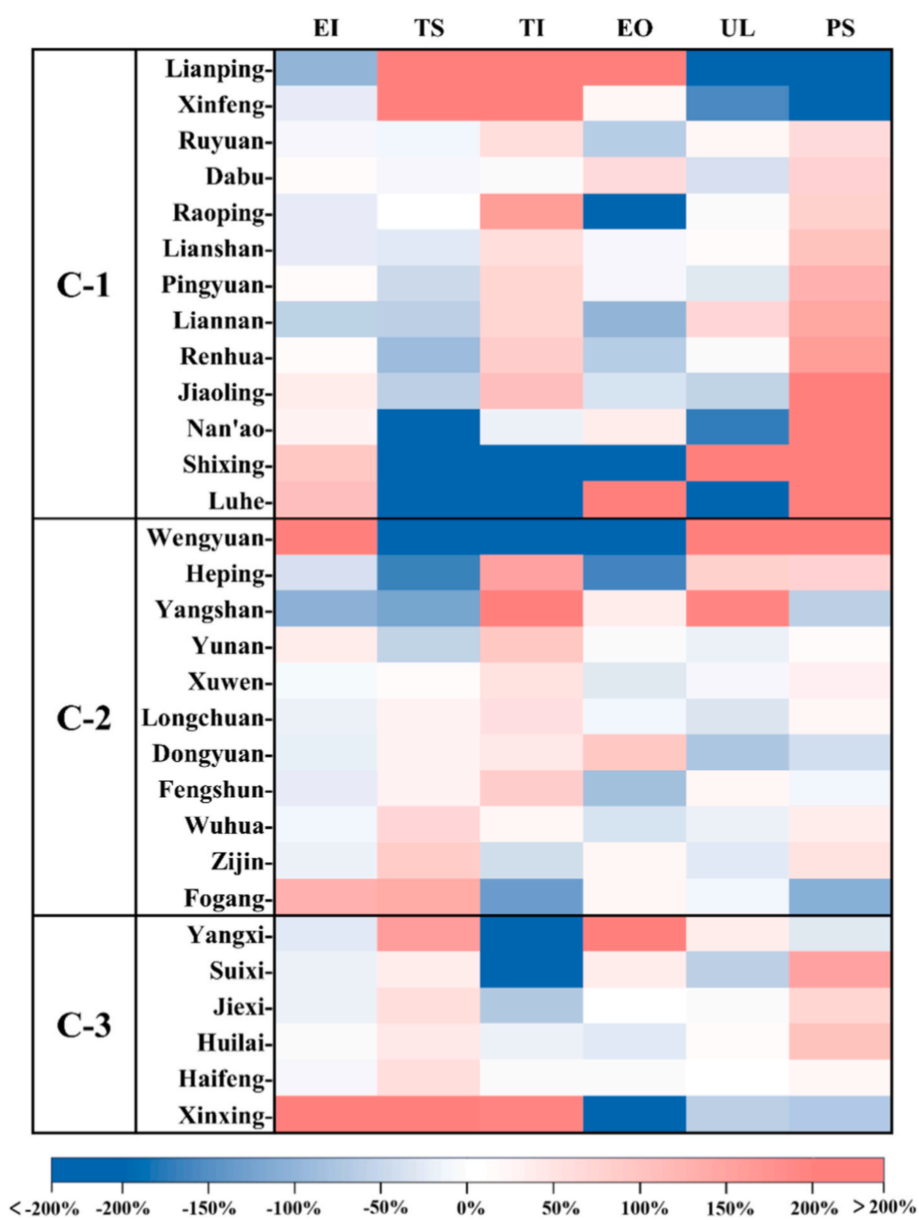

Fig. 6. Analysis of driving mechanism for differences in GHG emissions from RDW treatment among the investigated counties.

3.5. Driving mechanisms behind treatment-related GHG emission differences

The analysis of the LMDI decomposition results of GHG emissions from county-level RDW treatment reveals that the influence of the driving factors exhibits significant spatial heterogeneity (Fig. 6). Population size stands out as the primary drivers for the differences between the provincial average and county-level emissions. It positively affects the emission differences for 22 out of the 30 investigated counties. Particularly in C1, the less populated counties such as Lianshan, Pingyuan, Liannan and Nan'ao show more significant positive contributions of population size, with values of 97.4%, 125.0%, 149.4%, and 478.6%, respectively. A similar trend was also previously observed in cities with sparse populations, such as Lhasa and Hohhot, where the population size had great positive impacts on emission differences (Kang et al., 2022). These effects are primarily attributed to the fact that population growth substantially increases the total amount of RDW generation and thus elevates the treatment-related GHG emissions.

Treatment structure serves as another major contributor to the differences between provincial average and county-level emission. For example, in C1, the treatment structure in Nan'ao using only RDW incineration has a more obvious negative contribution (−308.2%) compared to landfill-based counties (Pingyuan, Lianshan, and Liannan) at around −50%, indicating that shifting from landfills to incineration helps reduce GHG emissions. This aligns with findings in Xi'an, where a high incineration rate led to the treatment structure making a negative contribution to emission (Kang et al., 2022). At the provincial level, Hainan's high incineration rate also significantly reduced emissions by 0.04 Mt CO_2e from 2019 to 2022 (Liu et al., 2025). Furthermore, it can be also found that the treatment intensity makes a negative contribution for most counties in C3. These counties have relatively higher levels of economic development, implying that economic development may strengthen the negative contribution of the treatment intensity on the emission differences. An existing study has confirmed that the treatment intensity was a mitigating factor for GHG emissions in Shanghai, which is consistent with the result in this paper (Xiao et al., 2021). Clearly, the disparity in the RDW treatment-related GHG emissions among the rural counties of Guandong are not only driven by population size, but also depend on the technical levels including treatment structure and treatment intensity.

The driving mechanisms can be explained as follows. Economically, rising GDP increase household consumption of packaged and plastic-rich goods, directly raising the plastic waste generation from C1 to C3 clusters. This compositional shift fundamentally alters emission potential. Under landfill, plastics are slow to degrade, generating negligible short-term CH_4. Under incineration, plastics release fossil-derived CO_2 at high intensity. Furthermore, TS determines which emission pathway is activated. In coastal counties, land scarcity and fiscal capacity drive incineration adoption, activating the plastic-to-CO_2 pathway. In contrast, landfill dominance activates the food waste-to-CH_4 pathway in inland counties, as food waste constitutes the majority of the waste stream. These two pathways lead to the fact that coastal per capita GHG emissions are 30% higher than inland. Besides, the effect of population size is more direct, simply scaling total waste volume.

3.6. Synergistic reduction analysis of RDW generation and its treatment-related GHG emissions

In order to depict the counties distribution on the synergistic degree between RDW generation reduction and treatment-related GHG emission reduction, a scatter diagram is presented in Fig. 7a. Dots in the first quadrant signify counties that have achieved the "positive-synergy" between the reduction of RDW generation and the reduction of GHG emissions. Dots in both the second and fourth quadrants denote "non-synergy", while those in the third quadrant represent "anti-synergy". As shown in Fig. 7a, only a small number of counties have attained "positive-synergy". Counties are predominantly distributed in the "anti-synergy" region, with only two counties showing "non-synergy". Fig. 7b illustrates the distribution of synergy types across different clusters and regions. In terms of variation among clusters, the proportion of positive-synergy cases rises substantially from 7.7% in C1 to 50% in C3. Across regions, this proportion declines from 66.7% in eastern Guangdong and 33.3% in western Guangdong to 19.0% in northern Guangdong. These patterns align closely with the economic development levels of the respective rural counties. More developed areas, such as counties in C3 and/or eastern Guangdong, exhibit the highest share of positive-synergy outcomes, implying that higher levels of economic development contribute to stronger synergistic effects. This observation is consistent with prior literature indicating that economic development significantly facilitates progress in carbon emission reduction (Xuan et al., 2020).

It is noteworthy that most counties achieving high synergy coefficients (△G/△W) have optimized their treatment structures by adopting incineration, which aligns with the LMDI decomposition results. For example, Raoping, Haifeng, and Xuwen, which rely heavily on incineration, achieved synergy coefficients of 0.94, 0.75, and 0.75, respectively. That is, for every 1 ton reduction of RDW, 0.94, 0.75, and 0.75 tons of CO_2e can be reduced in a coordinated manner. Existing research indicates that technological progress and industrial

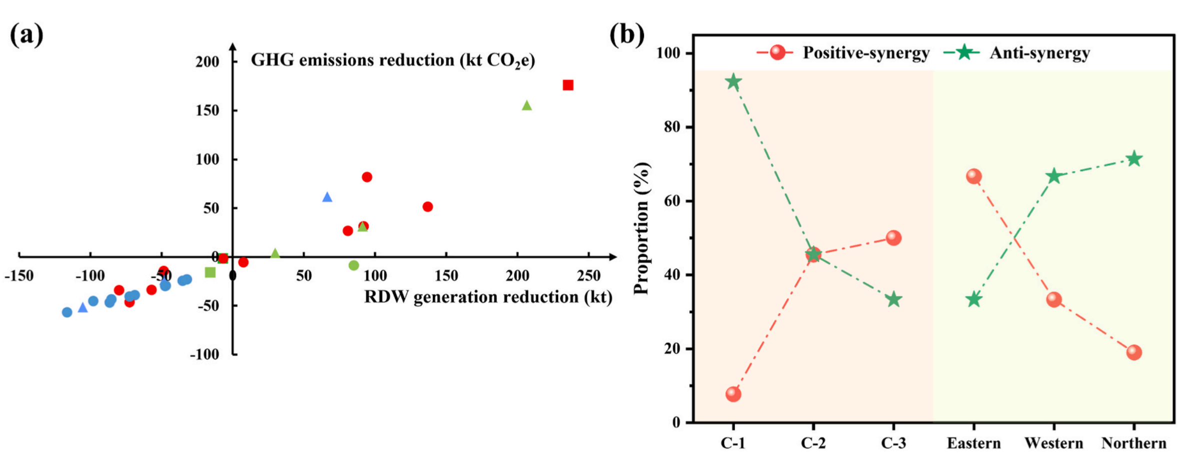

Fig. 7. Synergistic reduction degree of RDW generation and its treatment-related GHG emissions (RDW-GHG) across 30 counties: (a) counties distribution on RDW-GHG (shapes indicate regions: circle = north, triangle = east, square = west; colors indicate clusters: blue = C1, red = C2, green = C3), (b) proportion of synergy types in different clusters and geographical regions. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

restructuring are crucial pathways for enabling the co-reduction of CO_2 and pollutants (Chen et al., 2024). Therefore, in Guangdong's rural areas, progress in treatment technologies such as the expanding use of incineration, alongside economic development, is considered conducive to enhancing the synergistic reduction of RDW generation and treatment-related GHG emissions.

This positive synergy arises from two complementary pathways. First, incineration prevents the generation of high-GWP CH_4 that would otherwise be emitted during the long-term anaerobic decomposition of degradable components (e.g., food waste, paper, and wood) under landfilling. Given that CH_4 has a global warming potential 28 times that of CO_2, avoiding its release yields a substantial climate benefit. Second, modern incineration facilities equipped with energy recovery systems displace fossil fuel-based electricity, thereby avoiding additional CO_2 emissions that would otherwise occur from coal or natural gas power generation. The dual effect of methane avoidance and fossil fuel substitution constitutes the core of incineration-related synergistic reduction.

This mechanism also explains why positive synergy is more prevalent in economically developed counties (C3 and eastern Guangdong), where higher fiscal capacity and land scarcity drive the adoption of incineration over landfilling. In these counties, the combination of advanced treatment infrastructure and higher waste generation per capita amplifies the co-reduction effect. Consequently, the synergy effect is stronger in counties that have made this technological transition and increases with economic development level. These findings advance rural waste-carbon theory by demonstrating that treatment structure optimization is more influential than waste reduction alone, challenging the conventional policy focus on source reduction. Moreover, the synergy coefficient of 0.94, which is the first rural China quantification of emission reduction per unit waste reduction, provides a measurable benchmark for evaluating the climate benefits of shifting from landfilling to incineration in underdeveloped rural regions.

3.7. Sensitivity analysis

The sensitivity analysis reveals that the GHG emission estimates are most sensitive to the methane correction factor (C) and the degradable organic carbon content of food waste (D_{food}), with a $\pm10\%$ variation in these parameters leading to approximately $\pm8\%$ changes in total emissions, respectively. In contrast, the incineration efficiency (E) and compost emission factors (EF_C, EF_N) have relatively minor effects ($<\pm5\%$) due to the dominance of landfill in the treatment mix. Importantly, the spatial patterns (e.g., coastal vs. inland emission differences) and the relative rankings of counties by emission intensity remained stable across all sensitivity scenarios, supporting the robustness of our conclusions regarding spatial heterogeneity and driving mechanisms.

4. Discussion

4.1. Comparison with existing lists

Given the difficulty in obtaining and the lack of comprehensive statistics on RDW and its related greenhouse gas emissions in rural counties of Guangdong Province, this study established a county-level RDW generation and treatment inventory through bottom-up sampling and top-down investigation, and further developed a related greenhouse gas emissions inventory. A key advantage of this study is the use of field-based data collection from landfill and incineration facilities, combined with local government statistics, along with revised emission factors and the latest global warming potentials (GWPs). As a result, the results can more accurately mirror the local situation of RDW treatment when compared to inventories that rely on default factors or outdated parameters. Previous research has shown the importance of such methodological updates. Kang et al. (2022) reported that bottom-up estimates of municipal solid waste emissions were lower than China's 2018 United Nations Framework Convention on Climate Change (UNFCCC) submission (NDRC, 2018). This was mainly because of the outdated emission factors and GWPs in the earlier report. Similarly, another study verified that unrevised IPCC emission factors could overestimate waste-sector emissions by about 40% relative to locally updated values (Liu et al., 2015). High-resolution and localized data sources have also been demonstrated to yield greater accuracy (Wang et al., 2015; Zhao et al., 2019; Zhou et al., 2019). Cai et al. (2018), by using long-term datasets and IPCC FOD model, also obtained comparatively lower methane emission estimates.

Against this background, the findings show that 69.5% of RDW in the 30 investigated counties is disposed of in landfills. notably lower than the reported national average of 80% for China's rural areas (Bian et al., 2022). This difference aligns with Guangdong's relatively advanced economic development and its greater reliance on incineration facilities. None of the studied counties have implemented large-scale composting, and therefore GHG emissions from this treatment option could not be quantified. Moreover, comparative analysis with existing studies is constrained by the absence of reported RDW-specific GHG emission data for rural Guangdong, underscoring both the novelty and necessity of this study.

4.2. Policy impact

Research has demonstrated that government policy plays a more decisive role than GDP in management of solid waste (He et al., 2023). Following the implementation of the Rural Revitalization Strategy in China, rural areas have witnessed a significant increase in waste generation, which in turn highlights the substantial mitigation potential of the rural waste sector. Improving disposal technologies is essential to reducing GHG emission from RDW. For example, shifting treatment from landfills to incineration can substantially lower emissions, especially in regions where landfills remain dominant, which explains the recent rise in incineration shares. This trend is complicated, however, by the growing volume of plastic waste, as its incineration generates higher GHG emissions compared with landfilling in this study, underscoring the need for strengthened management strategies targeting plastics.

The spatial distribution of GHG emission drivers provides critical insights for targeted local policies. Based on our cluster analysis, we propose the following region-specific operational pathways. For C1 counties (mountainous, low GDP, landfill-dominated), priority should be given to collecting landfill gas and introducing treatment technologies. C2 counties are suitable for adopting a hybrid incineration-composting strategy to gradually shift from landfill while improving food waste separation. Coastal C3 counties (high GDP, incineration-oriented) should further increase incineration rates, but also reduce plastic use and improve incineration efficiency to enhance the synergy coefficient. Additionally, C3 counties can provide financial and technical assistance to less developed C1 counties, facilitating coordinated emission reduction across rural Guangdong.

Finally, population size serves as an amplifying factor for GHG emissions in both urban and rural areas. Addressing this requires not only technological and infrastructural improvements but also social measures—promoting low-carbon lifestyles, enhancing environmental education, and fostering public awareness. Unlike northern Chinese rural areas where coal-based heating dominates emissions, Guangdong's rural waste emissions demand consumption-side interventions alongside infrastructure optimization, offering a replicable framework for other transitioning provinces.

4.3. Limitations and further work

This study has certain limitations. First, the county-level RDW generation data used to compile the GHG emission inventory contain uncertainties. Although the RDW generation amounts in the 30 counties were mainly collected through on-the-spot research, the emission factors were obtained from the extensive review of Chinese and English literatures and relevant government reports. Due to restricted data accessibility, the default emission factors recommended by the IPCC were retained for certain categories, which may affect the accuracy of the estimates. A sensitivity analysis indicates that the total emissions vary by approximately $\pm 8\%$ in response to $\pm 10\%$ changes in the most influential parameters. While the absolute emission values carry this degree of uncertainty, the spatial patterns and relative rankings among counties were found to be robust across all sensitivity scenarios. Future studies should prioritize the development of region-specific emission factors for Guangdong's rural areas to reduce this uncertainty. Second, this study focused on a cross-sectional assessment for the year of investigation and thus provides limited insights into the temporal dynamics of RDW generation and associated GHG emissions in rural Guangdong. Third, although the harmless treatment rate for domestic waste in Guangdong Province has exceeded 99%, a very small number of cases involving open-air storage or random dumping may still exist. Therefore, our calculated RDW generation and GHG emissions are likely slightly lower than the actual values. The identified limitations highlight the need for future research aimed at enhancing the accuracy and robustness of GHG emission inventories for county-level RDW management. Future efforts should prioritize more comprehensive and standardized data collection, the development of region-specific emission factors, and the establishment of long-term monitoring systems. Integrating field surveys with emerging approaches such as remote sensing, big data analytics, and dynamic modeling could also help refine estimates and provide stronger support for policy and management.

5. Conclusion

Based on the systematic field survey across 30 underdeveloped counties in Guangdong, this study establishes high-resolution inventories of rural domestic waste (RDW) generation and its treatment-related greenhouse gas (GHG) emissions, amounting to 4031.2 kt of RDW and 2005.8 kt CO_2e. The inventories reveal that food (45.4%) and plastics (17.0%) dominate the waste stream, jointly accounting for 96.5% of treatment emissions. A distinct "low inland, high coastal" spatial pattern emerges, with coastal per capita emissions 30% higher than inland, confirming a cumulative emission effect driven by inadequate local disposal capacity as urban spillover support declines. Going beyond a purely descriptive inventory, this study integrates K-means clustering with spatial LMDI decomposition to uncover the drivers behind inter-county emission differences. Population size is the primary driver in mountainous counties experiencing out-migration (C1 cluster), whereas in economically advanced counties (C2 and C3), technical factors such as treatment structure and intensity play a stronger role, indicating that technological upgrading can effectively mitigate emissions. Moving from single-pollutant to synergistic accounting, we further quantify the co-reduction relationship between RDW reduction and GHG mitigation, for the first time in a rural waste context. The share of counties achieving positive synergy rises from 7.7% in the least developed (C1) to 50% in the most developed (C3) cluster. Treatment optimization, particularly the expanded use of incineration, achieves a synergy coefficient as high as 0.94, demonstrating that both technical efficiency and economic development level facilitate synergistic reductions. Collectively, these findings provide an empirical foundation for differentiated waste-carbon management policies and turn underdeveloped rural areas from data-scarce to data-driven, supporting both rural revitalization and regional climate goals.

CRediT authorship contribution statement

Yao He: Writing – original draft, Investigation. **Jie Zhang:** Writing – original draft, Investigation. **Chen Lin:** Investigation, Conceptualization. **Linlin Xia:** Writing – review & editing, Supervision. **Yazhuo Wang:** Writing – review & editing, Supervision. **Hewen Zhou:** Methodology. **Xun-an Ning:** Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the Key-Area Research and Development Program of Guangdong Province (2020B1111380001), Natural Science Foundation of Guangdong Province (2024A1515011468), National Natural Science Foundation of China (52476188), and Guangdong Provincial Key Laboratory of Renewable Energy (E539KF0101).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envpol.2026.128447.

Data availability

Data will be made available on request.

References

Ang, B.W., Xu, X.Y., Su, B., 2015. Multi-country comparisons of energy performance: the index decomposition analysis approach. Energy Econ. 47, 68–76. https://doi.org/10.1016/j.eneco.2014.10.011.

Bian, R., Zhang, T., Zhao, F., Chen, J., Liang, C., Li, W., Sun, Y., Chai, X., Fang, X., Yuan, L., 2022. Greenhouse gas emissions from waste sectors in China during 2006–2019: implications for carbon mitigation. Process Saf. Environ. Prot. 161, 488–497. https://doi.org/10.1016/j.psep.2022.03.050.

Cai, B.F., Lou, Z.Y., Wang, J.N., Geng, Y., Sarkis, J., Liu, J.G., Gao, Q.X., 2018. CH4 mitigation potentials from China landfills and related environmental co-benefits. Sci. Adv. 4. https://doi.org/10.1126/sciadv.aar8400.

Cai, H., Duan, Z., Lv, J., Zhou, L., Zhou, Q., Yan, Y., Long, J., Du, J., 2025. Assessing solid waste management effectiveness using the "Zero-waste Index" — exploration and practice in Chongqing. Circ. Econ. 4. https://doi.org/10.1016/j.cec.2025.100167.

Castell-Rüdenhausen, M.z., 2025. Material flow analysis and modelling of the feedstock potential for recycling polystyrene. Circ. Econ. 4. https://doi.org/10.1016/j.cec.2025.100127.

CEIC, 2024. Treatment rate of living waste: city: guangdong. https://www.ceicdata.com/en/china/treatment-rate-of-living-waste/cn-treatment-rate-of-living-waste-city-guangdong. (Accessed 20 April 2026).

Chen, Z., He, Y., Liao, N., 2024. Can carbon emission trading policy enhance the synergistic emission reduction of carbon dioxide and air pollutants? A comparative study considering different pollutants. Energy 305. https://doi.org/10.1016/j.energy.2024.132364.

Chen, S., Liu, J., Lin, Z., Lin, S., Li, L., Chen, Y., Evrendilek, F., Li, W., Huang, W., Yang, C., Yuan, H., He, Y., Dai, K., 2025a. Atmosphere-dependent pyrolytic transformability of glass fiber/epoxy resin composites in waste wind turbine blades. Chem. Eng. J. 505. https://doi.org/10.1016/j.cej.2025.159675.

Chen, Y., Liu, J., Li, L., Chen, X., Lin, Z., Yang, C., Evrendilek, F., Li, W., Huang, W., He, Y., Zhong, S., Yang, Z., 2025b. Optimizing pyrolysis of herbal tea and Salvia miltiorrhiza residues for sustainable energy and product recovery. Chem. Eng. J. 513. https://doi.org/10.1016/j.cej.2025.162694.

Cui, W., Wei, Y., 2024. Spatio-temporal evolution and the driving factors of municipal solid waste in Chinese different geographical regions between 2002 and 2020. Environ. Res. 240. https://doi.org/10.1016/j.envres.2023.117456.

Deng, M., Liu, H.-t., Ouyang, Z., 2022. Characteristics and driving factors of coastal rural domestic waste of the Yellow River Delta in China. J. Clean. Prod. 353. https://doi.org/10.1016/j.jclepro.2022.131670.

Fellner, J., Cencic, O., Rechberger, H., 2007. A new method to determine the ratio of electricity production from fossil and biogenic sources in waste-to-energy plants. Environ. Sci. Technol. 41, 2579–2586. https://doi.org/10.1021/es0617587.

Gao, X., Liu, N., Hua, Y., 2022. Environmental protection tax law on the synergy of pollution reduction and carbon reduction in China: evidence from a panel data of 107 cities. Sustain. Prod. Consum. 33, 425–437. https://doi.org/10.1016/j.spc.2022.07.006.

Guan, Y., Zhang, Y., Zhao, D., Huang, X., Li, H., 2015. Rural domestic waste management in Zhejiang Province, China: characteristics, current practices, and an improved strategy. J. Air Waste Manag. Assoc. 65, 721–731. https://doi.org/10.1080/10962247.2015.1010751.

Guan, Y., Kang, L., Shao, C., Wang, P., Ju, M., 2017. Measuring county-level heterogeneity of CO2 emissions attributed to energy consumption: a case study in

Ningxia Hui Autonomous Region, China. J. Clean. Prod. 142, 3471–3481. https://doi.org/10.1016/j.jclepro.2016.10.120.
Han, Z., Liu, D., Lei, Y., Wu, J., Li, S., 2014. Characteristics and management of domestic waste in the rural area of Southwest China. Waste Manag. Res. 33, 39–47. https://doi.org/10.1177/0734242X14558668.
Han, Z., Ye, C., Zhang, Y., Dan, Z., Zou, Z., Liu, D., Shi, G., 2019. Characteristics and management modes of domestic waste in rural areas of developing countries: a case study of China. Environ. Sci. Pollut. Control Ser. 26, 8485–8501. https://doi.org/10.1007/s11356-019-04289-w.
Han, Y., Wang, Y., Wang, X., Huang, J., Ma, W., 2024. Exploring the greenhouse gas emissions inventory and driving mechanisms of municipal solid waste in China. Environ. Impact Assess. Rev. 105. https://doi.org/10.1016/j.eiar.2024.107428.
He, H., Gao, X., Fei, X., 2023. Generation and management of municipal solid waste in top metropolitans of China: a comparison with Singapore. Circ. Econ. 2. https://doi.org/10.1016/j.cec.2023.100041.
He, Y., Li, N., Dong, M., Wei, S., Zhao, W., Gao, Y., Liu, H., Wang, W., Wang, T., Wang, K., Wang, S., Liu, D., 2026a. Enhancing light aromatics production by pre-cracking and enriching effect in catalytic pyrolysis of waste polypropylene over encapsulated ZSM-5@SBA-15 composites. Appl. Catal. B Environ. Energy 382. https://doi.org/10.1016/j.apcatb.2025.125917.
He, Y., Zhang, J., Huang, R., Li, N., Zheng, Y., 2026b. Effects of metal–acid proximity on aromatics production in CO2-Assisted catalytic pyrolysis of polypropylene over Fe-Modified ZSM-5. Journal 16, 270. https://doi.org/10.3390/catal16030270.
Huang, Q., Zhao, T., Lin, M., Li, W., Zhou, Q., Chen, C., 2025. Insights and practices for industrial solid waste management under "zero-waste city" construction in China. Circ. Econ. 4. https://doi.org/10.1016/j.cec.2025.100155.
IPCC, 2014. Climate change 2014 : mitigation of climate change : IPCC working group III contribution to AR5. Potsdam, Germany IPCC Work. Group III.
Jia, Z., Lin, B., 2021. How to achieve the first step of the carbon-neutrality 2060 target in China: the coal substitution perspective. Energy 233. https://doi.org/10.1016/j.energy.2021.121179.
Kang, Y., Yang, Q., Bartocci, P., Wei, H., Liu, S.S., Wu, Z., Zhou, H., Yang, H., Fantozzi, F., Chen, H., 2020. Bioenergy in China: evaluation of domestic biomass resources and the associated greenhouse gas mitigation potentials. Renew. Sustain. Energy Rev. 127. https://doi.org/10.1016/j.rser.2020.109842.
Kang, Y., Yang, Q., Wang, L., Chen, Y., Lin, G., Huang, J., Yang, H., Chen, H., 2022. China's changing city-level greenhouse gas emissions from municipal solid waste treatment and driving factors. Resour. Conserv. Recycl. 180. https://doi.org/10.1016/j.resconrec.2022.106168.
Kaza, S., Yao, L., Bhada-Tata, P., Woerden, F.V., 2018. What a Waste 2.0: a Global Snapshot of Solid Waste Management to 2050. World Bank, Washington, DC. https://doi.org/10.1596/978-1-4648-1329-0.
Kwon, Y., Choi, K., Jang, Y.-C., 2023. Greenhouse gas emissions from incineration of municipal solid waste in Seoul, South Korea. Energies 16. https://doi.org/10.3390/en16124791.
Li, H., Zhao, Y., Qiao, X., Liu, Y., Cao, Y., Li, Y., Wang, S., Zhang, Z., Zhang, Y., Weng, J., 2017. Identifying the driving forces of national and regional CO2 emissions in China: based on temporal and spatial decomposition analysis models. Energy Econ. 68, 522–538. https://doi.org/10.1016/j.eneco.2017.10.024.
Li, X., Bi, F., Han, Z., Qin, Y., Wang, H., Wu, W., 2019. Garbage source classification performance, impact factor, and management strategy in rural areas of China: a case study in Hangzhou. Waste Manag. 89, 313–321. https://doi.org/10.1016/j.wasman.2019.04.020.
Lin, S., Li, L., Wei, Z., Liang, J., Lin, Z., Evrendilek, F., He, Y., Ninomiya, Y., Xie, W., Sun, S., Liu, J., 2025. CO2-induced co-pyrolysis of Pennisetum hydridum and waste tires: multi-objective optimization of its synergies and pyrolytic oil, char and gas outputs. Energy 317. https://doi.org/10.1016/j.energy.2025.134670.
Liu, B., Rajagopal, D., 2019. Life-cycle energy and climate benefits of energy recovery from wastes and biomass residues in the United States. Nat. Energy 4, 700–708. https://doi.org/10.1038/s41560-019-0430-2.
Liu, Z., Guan, D., Wei, W., Davis, S.J., Ciais, P., Bai, J., Peng, S., Zhang, Q., Hubacek, K., Marland, G., Andres, R.J., Crawford-Brown, D., Lin, J., Zhao, H., Hong, C., Boden, T. A., Feng, K., Peters, G.P., Xi, F., Liu, J., Li, Y., Zhao, Y., Zeng, N., He, K., 2015. Reduced carbon emission estimates from fossil fuel combustion and cement production in China. Nature 524, 335–338. https://doi.org/10.1038/nature14677.
Liu, Y., Li, R., Cai, W., Liu, Q., 2025. Greenhouse gas emissions and mitigation strategies in China's municipal solid waste sector under the impact of the COVID-19 pandemic. Environ. Res. 266. https://doi.org/10.1016/j.envres.2024.120497.
Lou, Z., Cai, B.-F., Zhu, N., Zhao, Y., Geng, Y., Yu, B., Chen, W., 2017. Greenhouse gas emission inventories from waste sector in China during 1949-2013 and its mitigation potential. J. Clean. Prod. 157, 118–124. https://doi.org/10.1016/j.jclepro.2017.04.135.
Lu, C., Li, W., An, C., 2020. The GHG emission determinants research for waste disposal process at city-scale in baoding. Sustain. Cities Soc. 59. https://doi.org/10.1016/j.scs.2020.102203.
Mao, X., Zeng, A., Liu, S., Hu, T., Xing, Y., 2012. Assessment of SO 2, NO x and CO 2 co-control effects by technological reduction measures in iron & steel industry. Huanjing Kexue Xuebao/Acta Scientiae Circumstantiae 32, 1253–1260.
Meng, J., Yang, H., Yi, K., Liu, J., Guan, D., Liu, Z., Mi, Z., Coffman, D.M., Wang, X., Zhong, Q., Huang, T., Meng, W., Tao, S., 2019. The slowdown in global air-pollutant emission growth and driving factors. One Earth 1, 138–148. https://doi.org/10.1016/j.oneear.2019.08.013.
National Development and Reform Commission (NDRC), 2018. The People's Republic of China second biennial update report on climate change. http://big5.mee.gov.cn/gate/big5/www.mee.gov.cn/ywgz/ydqhbh/wsqtkz/201907/P020190701765971866571.pdf (Accessed 30 May 2026).
Su, B., Ang, B.W., 2012. Structural decomposition analysis applied to energy and emissions: some methodological developments. Energy Econ. 34, 177–188. https://doi.org/10.1016/j.eneco.2011.10.009.
Tian, G., Kong, L., Liu, X., Yuan, W., 2018. The spatio-temporal dynamic pattern of rural domestic solid waste discharge of China and its challenges. Environ. Sci. Pollut. Control Ser. 25, 10115–10125. https://doi.org/10.1007/s11356-017-1154-0.
United Nations Environment Programme, 2023. Emissions gap report 2023: broken record – temperatures hit new highs, yet world fails to cut emissions (again). Nairobi. https://doi.org/10.59117/20.500.11822/43922.
van Middelaar, C.E., Cederberg, C., Vellinga, T.V., van der Werf, H.M.G., de Boer, I.J.M., 2012. Exploring variability in methods and data sensitivity in carbon footprints of feed ingredients. Int. J. Life Cycle Assess. 18, 768–782. https://doi.org/10.1007/s11367-012-0521-9.
Wang, X., Nagpure, A.S., DeCarolis, J.F., Barlaz, M.A., 2015. Characterization of uncertainty in estimation of methane collection from select U.S. landfills. Environ. Sci. Technol. 49, 1545–1551. https://doi.org/10.1021/es505268x.
Wang, A., Zhang, L., Shi, Y., Rozelle, S., Osborn, A., Yang, M., 2017. Rural solid waste management in China: status, problems and challenges. Sustainability 9. https://doi.org/10.3390/su9040506.
Xiao, S., Dong, H., Geng, Y., Fujii, M., Pan, H., 2021. Greenhouse gas emission mitigation potential from municipal solid waste treatment: a combined SD-LMDI model. Waste Manag. 120, 725–733. https://doi.org/10.1016/j.wasman.2020.10.040.
Xuan, D., Ma, X., Shang, Y., 2020. Can China's policy of carbon emission trading promote carbon emission reduction? J. Clean. Prod. 270. https://doi.org/10.1016/j.jclepro.2020.122383.
Yang, Q., Zhou, H., Bartocci, P., Fantozzi, F., Mašek, O., Agblevor, F.A., Wei, Z., Yang, H., Chen, H., Lu, X., Chen, G., Zheng, C., Nielsen, C.P., McElroy, M.B., 2021. Prospective contributions of biomass pyrolysis to China's 2050 carbon reduction and renewable energy goals. Nat. Commun. 12. https://doi.org/10.1038/s41467-021-21868-z.
Zhao, Z., Bian, R., Zhao, F., Chai, X., 2019. Implications of municipal solid waste disposal methods in China on greenhouse gas emissions. Environ. Prog. Sustain. Energy 39. https://doi.org/10.1002/ep.13372.
Zheng, Y., Zeng, W., Chang, S., Wang, L., Liao, C., Zhang, Y., 2024. CO2 synergistic emission reduction and health benefits of PM2.5 reaching WHO-III level in Pearl River Delta. Atmos. Environ. 326. https://doi.org/10.1016/j.atmosenv.2024.120441.
Zhou, H., Meng, A., Long, Y., Li, Q., Zhang, Y., 2014. An overview of characteristics of municipal solid waste fuel in China: physical, chemical composition and heating value. Renew. Sustain. Energy Rev. 36, 107–122. https://doi.org/10.1016/j.rser.2014.04.024.
Zhou, S., Wei, W., Chen, L., Zhang, Z., Liu, Z., Wang, Y., Kong, J., Li, J., 2019. Impact of a coal-fired power plant shutdown campaign on heavy metal emissions in China. Environ. Sci. Technol. 53, 14063–14069. https://doi.org/10.1021/acs.est.9b04683.
Zhuang, Y., Wu, S.-W., Wang, Y.-L., Wu, W.-X., Chen, Y.-X., 2008. Source separation of household waste: a case study in China. Waste Manag. 28, 2022–2030. https://doi.org/10.1016/j.wasman.2007.08.012.