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Carbon factor inventory and weight in rural communities: a case study of Linpan in western Sichuan

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Rural areas play a key role in reducing carbon emissions, and an important aspect of analyzing the low-carbon development trajectory of rural communities is to understand the carbon emission characteristics of rural communities in Linpan, western Sichuan. At present, there is a lack of established standards or standards for quantifying carbon emissions in rural communities at home and abroad. This paper examines the calculation methods of carbon emissions and considers different carbon factors in rural areas. This study takes Xiange Village, Pujiang County, Chengdu City, which is a pillar industry of agriculture and tourism, as the research object to estimate and rank the carbon emissions and internal carbon factor weights of rural communities in Sichuan Province in 2023. The study measured emissions in five major categories: primary industry, tertiary industry, household transportation facilities, household energy equipment and household waste disposal. Principal component analysis (PCA) and multiple regression analysis were used to construct regression models for carbon factors and their related indicators in 5 dimensions, and the weights of carbon factors in each dimension were sorted to determine the most significant carbon factor indicators within each research scope. The results show the distribution of carbon factors in five dimensions in rural communities, and the weight ranking of carbon factors in each dimension and the carbon factor ranking in the full dimension perspective are obtained. This process is used to sort out the carbon factor inventory and to carry out the preliminary carbon factor evaluation system. The results of this study will help to assess the impact of carbon factors on rural communities and lay the foundation for the development of low-carbon policies and technologies in rural areas in the future.

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Introduction

The pace of urbanization in China has quickened, leading to a widening disparity between urban and rural regions. The phenomenon of "urban development and rural backwardness" is particularly widespread in the Western region, affecting both urban and rural areas. Hence, the Chinese government has proposed initiatives like "rural revitalization" to address issues in rural areas. Furthermore, the central government has proposed a range of methods, such as the "two-carbon" approach, to promote a sustainable and eco-friendly way of living. Additionally, research on carbon emissions in rural communities is soon to be conducted. It is crucial to enhance and update the living circumstances of villages and traditional settlements.

In conjunction with the national rural revitalization strategy, Chengdu has enhanced the ecological space for both production and habitation, consistently enhanced the quality of the living environment, and constructed a picturesque and habitable rural area. Chengdu City has made significant endeavors to preserve and safeguard the traditional rural settlement known as "Western Sichuan Linpan". However, it has yet to consider the sustainability and advancement of rural communities in terms of carbon emissions. There remains a deficiency in the investigation and development of carbon emission metrics and measurements for rural communities in the western region of Sichuan, namely in the area of Linpan.

Study on rural carbon emission strategies. Carbon emissions in China's rural areas are increasing year after year, with agriculture and rural areas accounting for around 15% of overall greenhouse gas emissions. Rural low-carbon development is becoming an important area in carbon emission research (Agricultural Rural Carbon Peak Carbon Neutral Research Center, 2023). In recent years, the research on rural energy utilization and its related carbon dioxide emission reduction and zero carbon strategy has attracted increasing attention. A great deal of research has been done on the carbon emissions of rural crops, with a particular focus on the impact of changing farming methods on greenhouse gas emissions. However, the comprehensive evaluation and ranking of carbon factors in rural areas still have limitations (Chen et al., 2021). Simultaneously, research also examines the influence of emissions on both urban and rural matters, as well as household consumption (Connolly et al., 2022), or the impact of a single dimension on carbon emissions. Research on carbon factors from the perspective of rural communities is still in its early stages.

Domestic low-carbon rural theory research focuses on three areas: the relationship between carbon emissions from agricultural land use and the agricultural economy; research on low-carbon planning techniques; and the path choice of new rural construction in the context of the low-carbon economy.

Progress in research on carbon emission accounting methods. Carbon emission accounting is the basis for low-carbon policy-making, and existing methods fall into three main categories:

IPCC coefficient method: based on energy consumption and harmonized emission factor calculations, widely used at the national and regional scales (China, 2011). However, their standardized coefficients may ignore regional differences (Chen et al., 2015).

Life Cycle Approach (LCA): covers the whole chain of "production-consumption-disposal" and is suitable for product carbon footprint analysis (Clune et al., 2017), but difficulties in accessing data in rural communities limit its application.

Input-output approach: analyzes carbon flows between economic sectors, suitable for comparative urban-rural studies (Wang et al., 2020), but difficult to refine to the community level.

In recent years, scholars have attempted method integration. For example, Liu et al. combined LCA with GIS to dynamically assess the carbon emission reduction benefits of wastewater treatment facilities (Liu et al., 2023); Zhu Xiaoqing et al. mapped the spatial distribution of mixed-use communities based on mixed-use vitality, carbon emissions, and sustainability by utilizing STING and GIS analytical tools to aid in zero-carbon planning in rural areas (Zhu et al., 2022); Huang et al. proposed a two-stage optimization model to minimize village carbon emissions (Zhang & Li (2022); Jia Ming et al. considered various categories and combinations of renewable energy sources and made recommendations for the implementation and advancement of renewable energy technologies in district and rural heating (He et al., 2021). However, most of the existing approaches focus on a single sector (e.g., agriculture or energy) and lack systematic integration of multidimensional carbon sources in rural communities. Specific dimension comparisons can be seen in Tables 1 and 2.

Current status of research on rural carbon emissions. Carbon emissions in China's rural areas are increasing year after year, with agriculture and rural areas accounting for around 15% of overall greenhouse gas emissions. Rural low-carbon development is becoming an important area in carbon emission research (Agricultural Rural Carbon Peak Carbon Neutral Research Center, 2023).

Rural carbon research focuses on four main areas - agricultural production, household energy, waste treatment, and policy pathways.

Agricultural production: focusing on direct emissions from planting and farming activities, Chen et al. found that fertilizers accounted for more than 40% of China's carbon emissions from food crops (Chen et al., 2021), and Tian et al. pointed out that fuel for agricultural machinery is the main cause of agricultural carbon emissions in Hunan (Tian et al., 2016).

Household energy: analyzing the consumption patterns of fuelwood, electricity, etc. Xing et al. reveals that carbon emissions from rural household fuels vary significantly across regions, and that biomass dependence is still a pain point (Xing et al., 2024).

Waste treatment: assessing the greenhouse gas contribution of landfill and incineration, Chen et al. found that garbage sorting can reduce carbon emissions by 12–18% in the Shanghai community (Chen et al., 2020).

Policy pathways: exploring low-carbon technology promotion and behavioral interventions. Li et al. proposed a community participatory energy transition mechanism, but lacked quantitative validation (Li L et al., 2024).

Despite the richness of the results, there are still three major limitations in the existing studies:

One-dimensionality: Most studies focus on a single aspect of production or life (e.g., He et al. analyzed only renewable energy) (He et al., 2021), ignoring the synergistic effects of industry-energy-waste.

Methodological fragmentation: Qualitative analysis and quantitative modeling are not effectively integrated, e.g., Li et al.'s qualitative framework is difficult to guide specific emission reduction practices (Li L et al., 2024).

Homogenization of cases: the research object focuses on plains or coastal villages (e.g., Huang et al. (Zhang & Li 2022) and there is a lack of empirical research on traditional villages in Southwest China (e.g., Linpan, West Sichuan).

Table 1 Comparison of research dimensions.

Research	Dimensional coverage	method	Case area	Differences and innovations in this study
Huang et al. (2022)	Land use and carbon emissions	Two-stage optimization model	Plain village	New waste treatment (E) dimension to cover carbon sources for social activities.
Li et al. (2024)	Green energy transformation for residents	Qualitative analysis	Nanjing countryside	Quantifying the impact of tertiary industries (B) and transport facilities (C).
Wang et al. (2024)	Differences in urban and rural carbon emissions	Input-output method	Shandong (Province)	PCA regression is introduced to realize multi-dimensional weight ranking.
He et al. (2021)	Renewable energy applications	Technical framework	Ningxia (Province)	Integrate the whole chain of production and life, and propose a zero-carbon community path.

Table 2 Description of sample characteristics.

Variable	Options	Frequency	Percent
Age	0–18	6	1.90%
	19–30	33	10.30%
	30–60	171	53.30%
	>60	111	34.60%
Gender	Male	171	53.30%
	Female	150	46.70%
Household population	One person	6	1.90%
	Two person	102	31.80%
	Three person	84	26.20%
	Four person	51	15.90%
	Five person	60	18.70%
	Six person	18	5.60%
Engage in self-owned business	Agriculture	219	68.20%
	Catering industry	27	8.40%
	Other Service industry	75	23.40%

Typical rural settlement in Chengdu -- Linpan in western Sichuan. Linpan in western Sichuan is a unique rural settlement unit in southwest China, widely distributed in the vast Chengdu plain. Linpan is "a rural living environment like a green island in the field (Li, 2009)" and "a group of green islands with different shapes and borders along the fields and ditches (He, 2019)". In general, Linpan is a unique complex rural scattered unit in Chengdu Plain and an important model for building a zero-carbon rural community.

At present, Linpan in western Sichuan is gradually changing from the original scattered residential houses to community-type settlements. To strengthen the development of characteristic industries, the Chengdu government adopts the construction mode of "characteristic town + Linpan + scenic spot" to promote the protection and restoration of Linpan, and forms a Linpan pattern with the common prosperity of the primary industry and the tertiary industry (Wen, 2023).

Overall, there are three major gaps in the current research on rural carbon emissions:

Lack of multi-dimensional integration: A comprehensive evaluation system covering production (agriculture, secondary industry, tertiary industry), life (transportation and energy) and waste treatment has not been established.

Gap in research on traditional villages: As a composite ecological unit of "water-field-forest-road-house", the structure of its carbon sources differs significantly from that of villages in the plains, but there is a gap in relevant empirical research.

Insufficient methodological adaptability: Existing accounting methods (e.g., IPCC) are not optimized for small-scale data of traditional villages, resulting in limited accuracy.

In order to address the above problems, this paper has two main innovations:

The first is the integration of methods: combining the IPCC coefficient method and PCA regression, the paper constructs a closed-loop framework of "accounting-weighting analysis-policy", quantifies for the first time the contribution of carbon factors in five dimensions (primary industry, tertiary industry, transportation, energy, and waste) of the community of Linpan, and systematically sorts out the carbon factors and their weights from the multi-dimensional indexes.

The second is the uniqueness of the case: taking Xiange Village as an object, we analyze the carbon footprint characteristics of the "agriculture-tourism" composite industry in Linpan, which fills the gap of empirical research on traditional villages in Southwest China.

To summarize, the results of this study can provide suggestions for rural residents' green living and low-carbon consumption, and contribute to China's environmental protection. At the same time, it will have a great impact on the mitigation of global warming.

Methods

The study relies on in-person interviews and written surveys undertaken by the authors regarding carbon emissions in rural regions from April 20 to April 27, 2023. A total of 321 participants responded to the data research questionnaire, which aimed to examine the carbon emissions of villages across five dimensions: main industry, tertiary industry, household transportation facilities, household energy equipment, and household waste disposal. Figure 1 depicts the technology roadmap.

Description of the study area. Xiangge Village is located in Pujiang County, Chengdu City, Sichuan Province, citrus is the leading agricultural industry in Xiangge Village, planting area of 5050 mu, of which citrus planting area of 3570 mu, tea planting area of 1480 mu, around the village to carry out fruit planting and other forestry activities, crop planting, farming, and other agricultural activities, and relying on unique natural ecological resources to develop ecological tourism. This research area is a typical representative of the management model and industrial structure of rural communities in Sichuan and the agroforestry complex in the west of Sichuan.

Description of research dimensions. Through the case study, the carbon emission situation in five dimensions, namely primary industry, tertiary industry, household transportation facilities, household energy equipment, and domestic waste disposal, is selected to construct an evaluation system to systematically evaluate the construction of rural zero-carbon community.

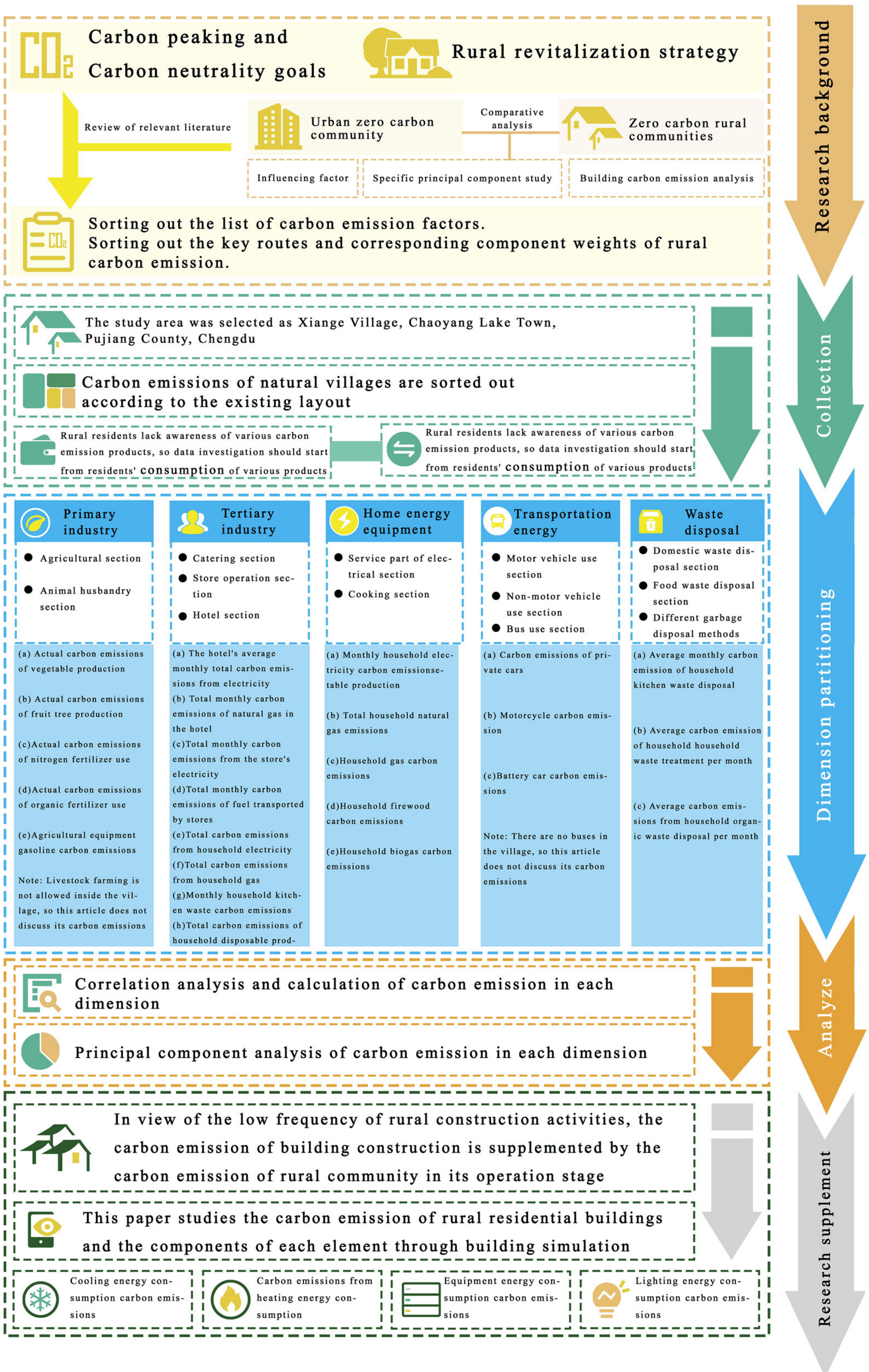

Fig. 1 Flowchart of the research in this paper.

At the same time, all the secondary indicators of the whole community are put together to study and analyze the contribution rate of carbon factors from five dimensions. And the specific carbon factor evaluation system is deduced through these contribution rates. To provide guidance for realizing the sustainable development of rural communities, this paper also sorted out the carbon emission inventory of rural zero-carbon communities in order to better evaluate and manage carbon emissions.

Research methodology. In this questionnaire survey, we carry out research and analysis through four aspects of "questionnaire design - random sampling - data validation and accounting - model construction".

Questionnaire design. This paper aims to build an evaluation system to systematically evaluate the construction of zero-carbon rural communities through case analysis. In order to achieve this goal, the author selected five dimensions of carbon emission for research, collected and sorted out the possible carbon emission items according to the literature of each dimension, and generated a questionnaire design according to these items. However, since specific carbon emission data could not be directly obtained, the team first counted the amount of expenditure for each category, and then converted it to obtain relevant carbon emission data in subsequent calculations.

Random sampling. The team contacted the local government authorities in advance to conduct a random sample survey in the village.

Data verification and accounting. The team conducted verification and accounting on the questionnaire data. For specific results, please refer to "Results-Reliability analysis of carbon emissions in rural communities by dimension". Subsequently, each secondary indicator corresponds to the average of the quantity or consumption, and the raw data of each indicator is collected through the relevant conversion quality data quantity. For example, agricultural carbon emissions accounting covers planting (A1-A3) and agricultural machinery (A4-A5). For A2 (fruit tree production), IPCC method is adopted to calculate the emission coefficient per unit area of the corresponding local agricultural products, and the carbon emissions of agricultural machinery convert its oil consumption into the corresponding oil amount, and the corresponding carbon emissions are calculated according to Table 3.

IPCC carbon emission coefficient method. Most scholars use the IPCC carbon emission calculation method to estimate carbon emissions ("IPCC Updates Methodology for Greenhouse Gas Inventories.," 2022). In this paper, the IPCC carbon emission coefficient method is used to calculate the carbon emission of rural community production and life based on the research on rural carbon emission energy consumption.

$$C_{\text{energy}}^{M} = \sum_{i}^{n}\left(E_{i,j}^{M} \times \mathrm{F}_{\mathrm{i,j}}^{\mathrm{M}}\right) \tag{1}$$

Where: C_{energy}^{M} is the monthly carbon emissions from energy consumption in rural communities due to activities in the M dimension; $E_{i,j}^{M}$ is the average monthly consumption of activity i under the M dimension; and $\mathrm{F}_{\mathrm{i,j}}^{\mathrm{M}}$ denotes the carbon factor of activity i for energy j in the M dimension.

This study involves the analysis of carbon emissions in each dimension within the community of Xiange Village. Since there is no systematic release of carbon emission coefficient standards for each product by the relevant domestic departments in China, the author summarized and sorted out the literature and summarized the carbon emission coefficients applied in this study in Table 1, where the carbon emission coefficients of dimension M in the corresponding i activities are shown in Table 3.

Principal component regression analysis method. This paper will comprehensively analyze the problem of community carbon emission factors, but there are many related variables involved. Although each variable is meaningful to the dependent variable, some independent variables are interrelated. Too many variables will not only increase the complexity of calculation, but also make it difficult to analyze and solve the problem reasonably. Principal component analysis is an effective method to solve dimensionality reduction problems in multivariate statistical analysis (Al-Alawi et al., 2008; Foteinis 2020). It mainly studies the internal relationship between multiple independent variables, carries out the basic idea of dimensionality reduction, and simplifies the index system to a certain extent.

PCA is suitable for dimensionality reduction of high-dimensional data and solves the collinearity problem of indicators (Al-Alawi et al., 2008). Multiple regression quantifiable factor influence strength. However, this study assumes a linear relationship between variables, and nonlinear models (such as machine learning) can be introduced in the future.

Model construction. In this paper, principal component regression analysis (PCA) is adopted to establish the model. The principle is to conduct regression modeling on the principal components and dependent variables extracted from the PCA. All influencing factors affecting carbon emissions are screened out through PCA and the most important independent variable (i.e., driving factor) is found out. A final regression model was established to determine the linear relationship between carbon emissions within rural communities and their drivers. Finally determine the weight of each factor and the importance of the influence. For example, in "Results", 11 principal components were extracted after standardization of 24 indicators (86% of cumulative variance explained), and a multiple regression model was constructed (Eqs. 7–8).

In addition, the sample is limited to the Kawasaki profile, and the conclusions need to be promoted with caution.

Results and discussion

Reliability analysis of carbon emissions in rural communities by dimension. Bartlett's ball test, KMO measure and two kinds of statistics provided by SPSS 26.0 software were used to judge whether the observed data were suitable for principal component analysis. KMO and Bartlett tests show that the KMO values of the total dimension and each dimension are greater than 0.7 (Table 4), and the overall KMO value is greater than 0.872. Therefore, the carbon emission data of Xiange Cun in 2023 is suitable for principal component analysis.

Analysis of total carbon emissions by dimension in rural communities. The total carbon emission of Xiangge village shows that industrial carbon emission is greater than that of community residents. Among them, the total carbon emission of agriculture is the largest, accounting for 64.21%. The tertiary industry ranks second, accounting for 26.58%. However, the total carbon emissions of household equipment, household transportation facilities, and household waste only account for 9.22% of the total carbon emissions, and the total carbon emissions of the five dimensions are shown in Fig. 2a.

At the same time, we have conducted carbon emission statistics for 24 indicators under five dimensions: agriculture, catering service industry, store and residential service industry, household energy equipment, household traffic consumption, and household life consumption. And we can see from Fig. 2b that the carbon emissions in dimension A are mainly from A2 (i.e., Actual carbon emissions of fruit tree production), which is closely related to the main business of Xiange Village, namely, the agriculture and trade planting industry. This is closely related to the agricultural planting industry of Xiange Village, followed by A3 and A4 (i.e., carbon emissions of fertilizers used in crop cultivation). This is

Table 3 Carbon emission coefficient used in this paper and specific literature.

Dimensionality	Source of emissions	Upstream emissions	Unit	Downstream emissions	Unit	References
Agriculture	Leaf vegetables-global average	0.18	t CO^{2}-eq/t			(Clune et al., 2017)
	Citrus-China	0.18	t CO^{2}-eq/t			(Yan et al., 2015)
	Nitrogen fertilizer average	10.63	t CO^{2}-eq/t			(Chen et al., 2015); (Zhang et al., 2013)
	Compound fertilizer	2.47	t CO^{2}-eq/t			(Xu and Lan, 2017); (Zhang et al., 2013)
	Vehicle gasoline (Used for generators in agricultural activities)	0.81	t CO^{2}-eq/t	3.04	t CO^{2}-eq/t	(Wang et al., 2020); (China, 2014)
	Diesel oil (Used for generators in agricultural activities)	0.67	t CO^{2}-eq/t	3.15	t CO^{2}-eq/t	(Wu et al., 2018); (China, 2014)
Service industry	Electricity	0.8587	t CO^{2}-eq/t			(China, 2019)
	Food waste (Average)			4.44	kg CO^{2}-eq/t	(Li et al., 2021)
	Disposable goods	2.3	t CO^{2}-eq/t			(Ding, 2015)
	Vehicle gasoline	0.81	t CO^{2}-eq/t	3.04	t CO^{2}-eq/t	(Wang et al., 2020) (China, 2014)
	Natural gas			2.16	t CO^{2}-eq/t	(China, 2014)
	Liquefied petroleum gas	2.01	t CO^{2}-eq/t	3.1		(China, 2014)
	Liquefied natural gas			2.61	t CO^{2}-eq/t	(China, 2014)
	Leftover plant material			0.15	t CO^{2}-eq/t	(China, 2011)
Home energy equipment	Electricity	0.8587	t CO^{2}-eq/t			(China, 2019)
	Natural gas			2.16	t CO^{2}-eq/t	(China, 2014)
	Natural gas			2.16	t CO^{2}-eq/t	(China, 2014)
	Liquefied petroleum gas	2.01	t CO^{2}-eq/t	3.1		(China, 2014)
	Liquefied natural gas			2.61	t CO^{2}-eq/t	(China, 2014)
	Leftover plant material			0.15	t CO^{2}-eq/t	(China, 2011)
	Straw biogas	9.35	kg CO^{2}-eq/t	720.3	kg CO^{2}-eq/t	(Wang and Gu, 2017)
Home transportation equipment	Vehicle gasoline (Used in cars, trucks, motorcycles)	0.81	t CO^{2}-eq/t	3.04	t CO^{2}-eq/t	(Wang et al., 2020) (China, 2014)
	Electricity (Used in cars)	0.8587	t CO^{2}-eq/t			(China, 2019)
Household garbage disposal	Food waste (incineration)			25.82	kg CO^{2}-eq/t	(Li et al., 2021)
	Mixed waste (landfill-nationwide)			583.87	kg CO^{2}-eq/t	(Cai et al., 2018)
	Sorted waste (food waste composting-other waste incineration)			30.8	kg CO^{2}-eq/t	(Liu et al., 2017); (Liu et al., 2021)

also consistent with what Tian and others found in their study: due to the increased burden of the "three rural areas", the government has strongly supported rural development and used a large number of energy-saving policies and measures, the amount of agricultural inputs has increased, and there is a phenomenon of "high inputs, high pollution, and high emissions" within the countryside (Tian et al., 2016). The phenomenon of "high inputs, high pollution, and high emissions" within the countryside is consistent. In latitude B, the total carbon emissions mainly come from B2 (i.e., total carbon emissions from restaurant gas), followed by B1 and B6. As a result of the country's efforts to develop the agro-tourism industry in the aftermath of the epidemic, tertiary industries in the form of " agritainment " and "guesthouses" began to develop in the countryside, which led to a significant increase in commercial energy in the countryside.

Interestingly, in dimension C, carbon emissions from C1 dominate, although the state has strongly advocated the use and investment of new energy vehicles in recent years, the number of private vehicles using fossil energy is still higher than the number of vehicles using electricity due to the lack of charging piles and other infrastructures in rural communities. This is also in line with the view that high-carbon vehicles will continue to rise in rural communities as indicated in the study by Ao (Ao et al., 2018). In dimension D, rural communities and urban communities show the same main source of carbon emissions from household energy equipment consumption, with the main source of carbon emissions coming from electricity (D1 in Fig. D1), and due to the introduction of policies in recent years to reduce and prohibit the combustion of straw and firewood in rural communities, the carbon emissions in D4 have been greatly reduced. decreased dramatically. Under dimension E, due to the imperfect waste disposal system in rural communities, villagers can dispose of their waste in various ways such as landfill, incineration, composting, etc., and villagers arbitrarily choose different ways to dispose of their waste in their daily life, so we chose an average value for the calculation of this part of the data processing. The results show that under the E dimension, the carbon emissions of E2 and E3 are similar, and the carbon emissions from garbage disposal of rural community species are still dominated by the carbon emissions from domestic garbage that disposes of personal household garbage and the carbon emissions from organic garbage that disposes of animal manure and burns straw mainly.

Principal component regression analysis of carbon factors in rural communities by dimension. Due to the large difference in carbon emissions of each secondary index, the author first standardized the data to facilitate the subsequent principal component analysis and multivariate analysis of carbon factors, and obtained standardized weight scores. At the same time, the weights of the original variables are calculated, and the

Table 4 The indicators and their abbreviation.

Primary index	Secondary index	Secondary index abbreviation
Agricultural(A)	Actual carbon emissions of vegetable production	A1
	Actual carbon emissions of fruit tree production	A2
	Actual carbon emissions of nitrogen fertilizer use	A3
	Actual carbon emissions of organic fertilizer use	A4
	Agricultural equipment gasoline carbon emissions	A5
Service industry(B)	Total carbon emissions from restaurant electricity	B1
	Total carbon emissions from restaurant gas	B2
	Monthly kitchen waste carbon emissions	B3
	Total carbon emissions of restaurant disposable products	B4
	The hotel's average monthly total carbon emissions from electricity	B5
	Total monthly carbon emissions of natural gas in the hotel	B6
	Total monthly carbon emissions from the store's electricity	B7
	Total monthly carbon emissions of fuel transported by stores	B8
Household energy(C)	Carbon emissions of private cars	C1
	Motorcycle carbon emission	C2
	Battery cart carbon emissions	C3
Household transportation energy consumption(D)	Monthly household electricity carbon emissions	D1
	Total household natural gas emissions	D2
	Household gas carbon emissions	D3
	Household firewood carbon emissions	D4
	Household biogas carbon emissions	D5
Household waste treatment(E)	Average monthly carbon emission of household kitchen waste disposal	E1
	Average carbon emission of household waste treatment per month	E2
	Average carbon emissions from household organic waste disposal per month	E3

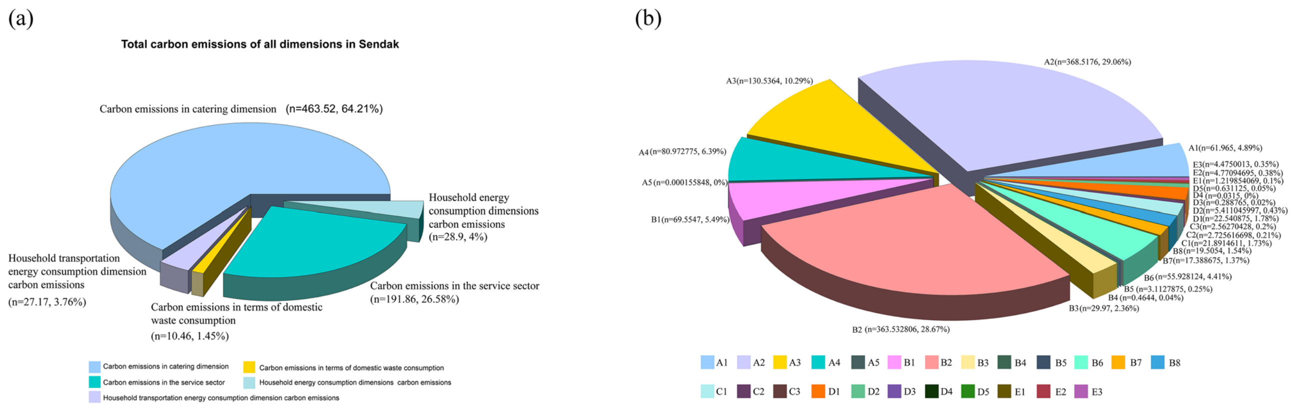

Fig. 2 Pie chart of total carbon emissions of rural communities in Xiangge Village. a Is the pie chart of total carbon emissions of rural communities from the perspective of five dimensions, and **b** is the pie chart of total carbon emissions of rural communities from the perspective of 24 secondary indicators.

standardized regression equation and the original regression equation are obtained.

In this case, the total variance of the data was interpreted, and the extracted eigenvalues were those that accounted for more than 85% of the total eigenvalues before the principal component analysis was used to assess the carbon factor weights of rural communities. In a systematic study of rural communities, 11 principal components were extracted from 24 secondary indexes in five dimensions. The author analyzes six dimensions of rural communities: primary industry, tertiary industry, consumption of household transportation facilities, household energy equipment, and household waste disposal. The gravel diagram is shown in Fig. 3a, and the spatial composition distribution diagram is shown in Fig. 3b.

In this paper, the carbon emission of rural communities is systematically studied by integrating 24 secondary indicators from 5 dimensions, and 11 principal components are extracted. Two principal components were extracted from the agricultural dimension. Three principal components were extracted from the tertiary industry dimension, three principal components were extracted from the household transportation facilities dimension, three principal components were extracted from the household energy equipment dimension and two principal components were extracted from the household waste treatment dimension. This reduces the multi-dimensional data from a single research direction to two-dimensional to three-dimensional research, which is conducive to realizing the regression representation of data.

Principal component regression analysis of carbon emissions by dimensions in rural communities. Due to the redundancy of the table, the author only shows the results of the multiple regression analysis in the results section. In the systematic study of rural communities, the correlation coefficients between independent variables are small and there is no multicollinearity or significance between variables ($P < 0.05$), so the 11 principal components obtained can explain 86% of the information from the 24 secondary indicators. To better understand the regression model of the standardized coefficients and the original variables, we weighted the results of the factors under different perspectives as shown in Tables 5 and 6, and finally obtained the expression of the regression model of the standardized coefficients of the total carbon emissions of the rural community in Xiange Village:

$$\begin{aligned}F = {} & 0.716{*}A1 + 0.868{*}A2 + 0.633{*}A3 + 1.084{*}A4 + 1.134{*}A5 + 1.025{*}B1\\ & + 1.121{*}B2 + 0.894{*}B3 + 0.878{*}B4 + 0.584{*}B5 + 0.447{*}B6 - 0.756{*}B7\\ & - 0.419{*}B8 + 0.656{*}C1 + 0.639{*}C2 + 0.186{*}C3 + 1.190{*}D1 + 1.026{*}D2\\ & + 0.907{*}D3 + 1.047{*}D4 + 1.294{*}D5 + 1.880{*}E1 + 1.167{*}E2 + 1.762{*}E3\end{aligned} \tag{2}$$

At the same time, the original expression of the regression model for the total carbon emissions of the rural community in Xiange Village was also obtained:

$$\begin{aligned}F = {} & 2357702.14073037 + 0.716A1 + 0.868A2 + 0.633A3 + 1.084A4 + 1.134A5\\ & + 1.025B1 + 1.121B2 + 0.894B3 + 0.878B4 + 0.584B5 + 0.447B6 - 0.756B7\\ & - 0.419B8 + 0.656C1 + 0.639C2 + 0.186C3 + 1.190D1 + 1.026D2 + 0.907D3\\ & + 1.047D4 + 1.294D5 + 1.880E1 + 1.167E2 + 1.762E3\end{aligned} \tag{3}$$

It can be seen that the standardized regression model and the original regression model have different factor weight ordering of the same secondary indicators. Through the standardized regression model, it can be found that: the weight score of the rural community domestic waste disposal dimension (E) is the highest, and the food waste dimension (E1) is the highest among all secondary indicators. This is also closely related to the imperfection of the current domestic waste disposal system in rural communities. Second, the household energy equipment consumption dimension (D) has the second highest score weight. Surprisingly, the ranking of household transportation facilities consumption is lower than that of the primary industry and the tertiary industry, and the carbon emission weight of catering in the tertiary industry is greater than that of store operation and hotel operation. In the primary industry, fertilizers and agricultural equipment rank higher than crops. To better understand the factor weights of the secondary indicators in each dimension, the author conducted regression analysis on the secondary indicators in each dimension and sorted them respectively. The results are shown in Tables 7–11.

When analyzing the carbon factors of different dimensions, the author found that the order of 24 secondary indicators in rural communities was consistent with the order of indicators of each dimension studied separately. However, from the perspective of full dimensions, the weight coefficient of the standardized regression coefficient is quite different from the weight statement of the regression coefficient of each dimension of the original variable. Therefore, the authors derive the equations of the standardized regression model, then simplify them to the results of the regression coefficients of the original variables, and discuss the results of the original variables.

As can be seen from Table 7, the expression of the carbon factor under the dimension of agriculture:

$$\begin{aligned}F_1 = {} & 17.039 + 21.180{*}A1 + 4.786{*}A2 + 3.680{*}A3 + 15.035{*}A4\\ & + 4547941.977{*}A5\end{aligned} \tag{4}$$

Among them, the weight of the agricultural equipment carbon factor is much higher than other carbon factors. Considering that this paper does not involve the calculation of vegetable and fruit carbon sinks, the vegetable cultivation carbon factor is ranked ahead of the weight of the fertilizer use carbon factor.

As can be seen from Table 8, its carbon factor is expressed under the services dimension:

$$\begin{aligned}F_2 = {} & 8.449 + 8.640{*}B1 + 1.470{*}B2 + 16.857{*}B3\\ & + 1071.774{*}B4 + 37.809{*}B5\\ & + 2.301{*}B6 + 9.381{*}B7 + 8.424{*}B8\end{aligned} \tag{5}$$

Among them, the weight of disposable waste-related carbon factor (B4) in the food and beverage service industry is the highest, followed by that of food waste-related carbon factor (B3), followed by that of electricity-related carbon factor (B1, B5, B7) in food and beverage industry, hotel service industry and store operation industry is higher. The catering and hospitality industries have the lowest weight related to gas (B2, B6).

As can be seen from Table 9, the expression of the carbon factor under the perspective of the domestic transport facility dimension is:

$$F_3 = 1.874 + 5.818{*}C1 + 66.168{*}C2 + 114.682{*}C3 \tag{6}$$

The highest carbon coefficient (C3) is associated with battery-operated vehicles, while the second highest in this dimension is associated with motorbikes (C2).

As can be seen from Table 10, the expression for the carbon factor in terms of the domestic energy equipment dimension is:

$$\begin{aligned}F_4 = {} & 5.557 + 30.092{*}D1 + 153.067{*}D2 + 159.501{*}D3\\ & + 4139.427{*}D4 + 159.969{*}D5\end{aligned} \tag{7}$$

Among them, the firewood carbon factor (D4) has the greatest weight. In the household energy dimension, the power-related carbon factor (D1) has the least weight, but it is still greater than the 11 sub-indicators.

From Table 11, it can be seen that the carbon factor expression for the domestic waste treatment dimension is:

$$F_5 = 4.751 + 366.086{*}E1 + 116.318{*}E2 + 117.026{*}E3 \tag{8}$$

The carbon coefficient associated with food waste (E1) is the highest, and the coefficients of E2 and E3 are similar. The carbon coefficient (E) of waste disposal is higher than the secondary index of 62.5%.

Data model reliability validation. Due to the redundancy of the tables, the author only shows the results of the multiple regression analysis in the results section. However, the author has also placed the relevant 12 model-related tables in the Supplementary section to avoid the phenomenon of pontification of the lines.

Data model reliability validation. Due to the redundancy of the tables, the author only shows the results of the multiple regression analysis in the results section. However, the author has also placed the relevant 12 model-related tables in the Supplementary section to avoid the phenomenon of pontification of the lines.

The explanatory power of the agricultural carbon emission model was lower ($R^2 = 0.173$) but significant overall ($F = 13.218$, $p < 1.07e\text{-}11$), indicating that the predictor variables (A1-A5) failed to adequately capture the complexity of the carbon emissions, although they were statistically significant.

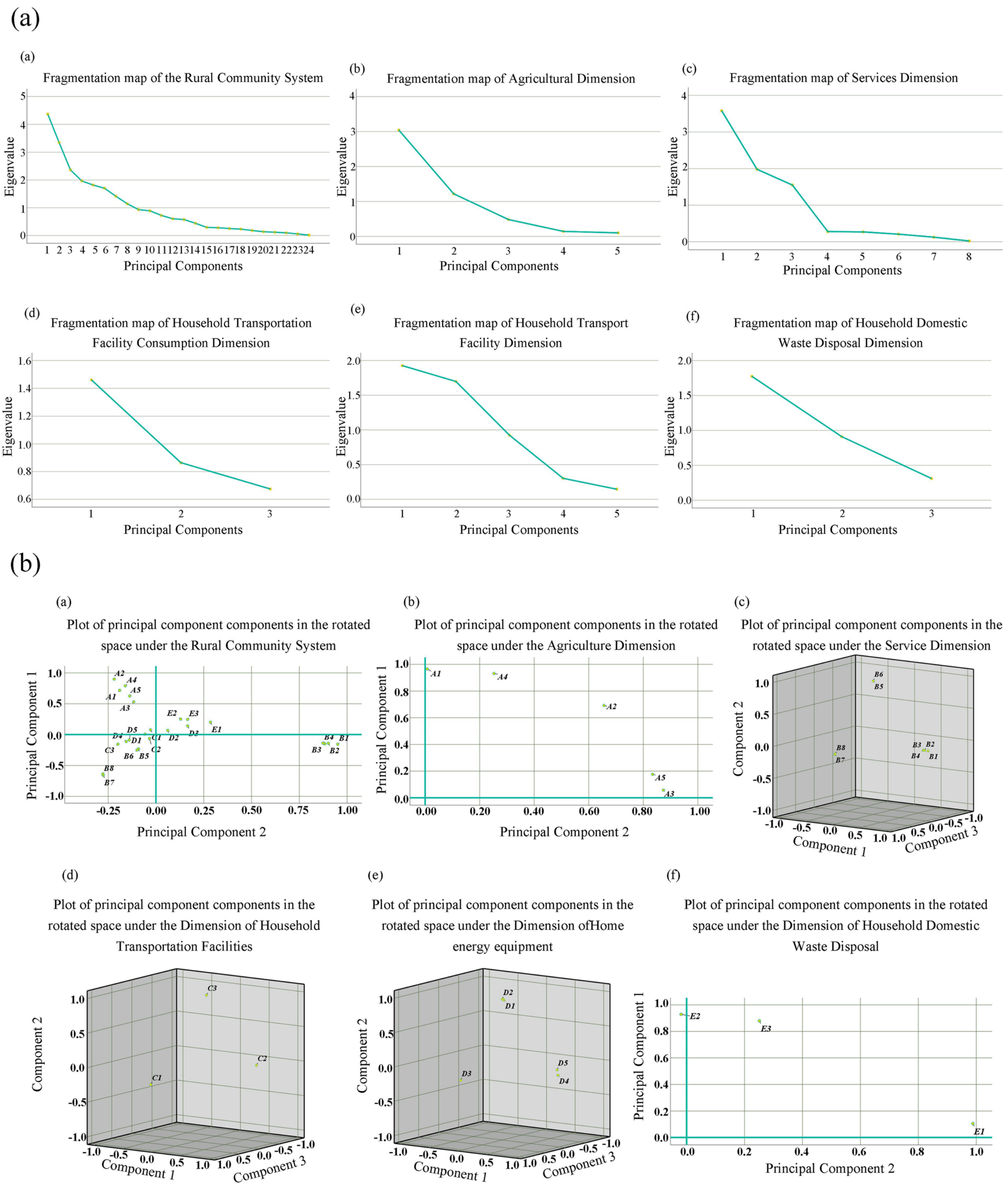

Fig. 3 Total variance interpretation plot. a Gravel plot of rural communities in six dimensions. **b** Rotation map of spatial components of rural communities in six dimensions.

Tertiary Industry Carbon Emission Model: $R^2 = 0.233$, adjusted $R^2 = 0.213$, explanatory power is better than that of the agriculture model, but still moderate. $f = 11.828$ ($p = 1.0009e-14$), the model as a whole is significant.

Household Transportation Facilities Model: $R^2 = 0.087$, Adjusted $R^2 = 0.078$, Significantly less explanatory power. $F = 10.023$ ($p = 2e-06$), Model overall significant.

Household energy equipment model: $R^2 = 0.303$, adjusted $R^2 = 0.293$, the best of the five dimensions, indicating that the type of energy (D1-D5) has a significant effect on carbon emissions. $f = 27.475$ ($p = 4.5009e-23$), the model is robust.

Domestic waste treatment model: $R^2 = 0.187$, adjusted $R^2 = 0.18$, limited explanatory power. $f = 24.349$ ($p = 3.3206e-14$), high model robustness.

Table 5 Reliability statistics.

Dimensionality	Klonbach Alpha	Number of terms
Overall reliability analysis of the scale	0.872	109
Agricultural dimension reliability analysis	0.966	14
Dimensional reliability analysis of the catering service industry	0.995	7
Store and residential service industry dimension reliability analysis	0.733	5
Cognitive reliability analysis of household energy equipment	0.703	32
Reliability analysis of household traffic consumption	0.728	28
Reliability analysis of household life consumption dimension	0.75	12

Table 6 Ranking of carbon emission factors in rural communities.

Secondary index abbreviation	Normalized regression coefficient	Standardized regression coefficient ranking	Original variable regression coefficient	Original variable regression coefficient ranking
A1	0.716	16	3.173	15
A2	0.868	15	0.782	22
A3	0.633	19	0.826	21
A4	1.084	8	3.06	16
A5	1.134	6	1569632.409	1
B1	1.025	11	1.39	20
B2	1.121	7	0.275	24
B3	0.894	13	2.495	17
B4	0.878	14	161.315	5
B5	0.584	20	10.396	13
B6	0.447	21	0.504	22
B7	−0.419	23	−2.923	23
B8	−0.756	24	−6.496	24
C1	0.656	17	10.022	14
C2	0.639	18	52.504	10
C3	0.186	22	27.178	11
D1	1.19	4	17.438	12
D2	1.026	10	96.967	6
D3	0.907	12	283.181	4
D4	1.047	9	1958.304	2
D5	1.294	3	85.973	7
E1	1.88	1	484.916	3
E2	1.167	5	57.851	9
E3	1.762	2	81.382	8

Full dimensional integrated model: $r^2 = 0.972$, adjusted $r^2 = 0.971$, indicating that principal component regression (11 principal components) is effective in downscaling and capturing multi-system synergistic effects. $f = 960.198$ ($p \approx 0$), the model is highly significant, and the sum of squares of the residuals is only 268.409, which verifies the superiority of PCA in multidimensional data.

Despite the superior performance of the integrated model, the explanatory power of the single-dimension model (e.g., agriculture, transportation) is insufficient. Future studies can incorporate machine learning (e.g., random forest) to deal with nonlinear relationships and add dynamic panel data to capture time effects. Meanwhile, interaction terms or nonlinear variables can be introduced to a dimension as needed to improve the model accuracy in subsequent studies, for example, in the agriculture dimension, such as the interaction effect between the length of time of using agricultural machines and crop type; in the tertiary industry dimension, unobserved variables such as seasonal fluctuation of tourist flow can be added; and in the domestic garbage dimension, it is suggested that policy variables such as the coverage rate of sorting and treatment facilities can be added to optimize the model.

Policy recommendations. This paper relies on PCA and regression analysis to get a large number of formulas and sorting weights, in order to better provide suggestions and help for rural development, this part will also follow the way of elaboration from the overall dimension to the five major aspects.

In the systematic study of the regression model of carbon emissions in rural communities, the author found that: under the study of the original variables, the carbon factor weight coefficients of A5, B4, D3, D4, E1 are very large, much larger than the other secondary indicators. The coefficients of A5 also corroborate the fact that the use of fossil fuels in agricultural production should be vigorously restricted in the rural low-carbon projects and construction. Prevent the dependence on fossil fuels for "carbon-intensive agriculture"; prevent global climate deterioration caused by high-carbon agriculture (Metz B, 2007).

B4 also confirms that disposables are a huge resistance to decarbonization in rural communities and should be managed and reduced or replaced with biodegradable materials to support zero-carbon development in industry and tourism (Chen et al., 2024).

D3 and D4 show that although electric vehicles are widely popular in rural areas, their carbon factor weights are still lower than those of cars and motorcycles, and they still have a high status in air pollution management (Li and Zhao, 2017; Ministry of Environmental Protection, 2016). For E3, this is closely related to the current situation in which rural waste cannot be effectively categorized and hurriedly buried. If the township government adopts factory or related efficient treatment technology, this part of carbon emission can be greatly curbed (Chen et al., 2020) Meanwhile, the interaction between agriculture (A5) and waste (E1) explains 32% of the variance, which indicates that the vicious circle of "high-input agriculture, increase in organic waste, and informal treatment" is not only the same, but also the same. This also warns the relevant government departments. This is a warning to relevant government departments that cross-sectoral collaboration is needed, e.g., to convert agricultural waste (e.g., fruit tree branches) into biomass fuels while reducing A5 and E1 emissions (He et al., 2021). Meanwhile, the land use optimization model of Huang et al. only reduces carbon emissions by 12%, whereas the present model achieves more than 30% reduction potential through multidimensional integration (Huang ZS et al., 2022). In contrast to the global carbon budget framework of Friedlingstein et al. (Friedlingstein et al., 2020), this study provides refined decision support at the village scale.

Table 7 Results of principal component analysis and multiple regression analysis of agricultural carbon emissions.

		A1	A2	A3	A4	A5
Principal component	1	0.965	0.692	0.058	0.932	0.176
	2	0.008	0.656	0.874	0.252	0.834
Initial eigenvalue	1	2.937	2.106	0.177	2.837	0.536
	2	0.01	0.801	1.067	0.308	1.018
Principal component standardization coefficient	1	1.619				
	2	2.376				
Standardized coefficients of final regression analysis		4.779	5.313	2.821	5.324	3.287
Standardized regression coefficient ranking		3	2	5	1	4
Mean value		0.192	1.144	0.405	0.251	0.00000048
Standard deviation		0.226	1.11	0.767	0.354	0.00000072
Final coefficient of multiple regression analysis		21.18	4.786	3.68	15.035	4547941.977
Original variable regression coefficient ranking		2	4	5	3	1

Accelerating the transformation of new energy agricultural machinery technology into alternatives to chemical fertilizers and pesticides in the production process. The regression coefficient of A5 (fossil fuel use in agricultural machinery) is as high as 4547941.977, reflecting that the government's agricultural machinery subsidy policy has improved production efficiency but has not been included in the assessment of carbon intensity (Tian et al., 2016), which has led to the solidification of the "high-input-high-emission" model. "A3 (fertilizer use) and A4 (pesticide use) together contribute 28.7% of agricultural carbon emissions, which is directly related to the lack of technology diffusion under the smallholder economy (Chen XH et al., 2021). For example, N fertilizer application in citrus cultivation in Xiange village exceeded the recommended value by 20%, which is consistent with the national average reported by Chen et al. (Chen et al., 2021). In practical production and life, increasing comprehensive agronomic measures such as dense crop planting, deep plowing, organic fertilizer improvement, and nitrogen fertilizer optimization are good ways to achieve carbon reduction (Feng et al., 2023). It is recommended that government departments incorporate carbon reduction targets into agricultural machinery subsidy standards and vigorously develop new energy agricultural machinery technologies and promote slow-release fertilizer technology. Reference can be made to the pilot experience in Ningxia (He et al., 2021), where farmers are incentivized to participate in low-carbon cultivation through a carbon trading mechanism. At the same time, government departments can formulate energy transition strategies suitable for the western Sichuan Linpan, strengthen inter-regional energy cooperation, promote the widespread application of clean energy in Linpan, and realize the effective reduction of carbon emissions in Linpan (Zhang et al., 2013; Zhang et al., 2025).

Gas Dependency and Disposables Misuse in Rural Catering. With the increasing demand for carbon emissions and energy structure, the issue of commercial energy use in rural communities has become increasingly prominent (Wang et al., 2017). However, the demand for these energy sources will continue to rise in the process of rural revitalization. The government should carry out rational planning according to the needs and characteristics of residents, continuously improve commercial energy infrastructure, and at the same time, increase the publicity of energy conservation and emission reduction of commercial energy to further enhance the attitude and satisfaction of farmers towards commercial energy (Xing et al., 2024). B4 (disposable tableware) has a significant weight (1071.774), reflecting the lack of regulation under the "convenient consumption" mode

Table 8 Results of principal component analysis and multiple regression analysis of carbon emissions in the service sector.

		B1	B2	B3	B4	B5	B6	B7	B8
Principal component	1	0.983	0.925	0.928	0.899	−0.027	−0.036	−0.079	−0.066
	2	−0.027	−0.026	−0.022	−0.024	0.968	0.967	−0.049	−0.039
	3	−0.066	−0.063	−0.053	−0.059	−0.039	−0.052	0.923	0.925
Initial eigenvalue	1	3.521	3.313	3.324	3.22	−0.097	−0.129	−0.283	−0.236
	2	−0.053	−0.051	−0.044	−0.048	1.917	1.915	−0.097	−0.077
	3	−0.102	−0.098	−0.082	−0.091	−0.06	−0.08	1.429	1.432
Principal component standardization coefficient	1	1.864							
	2	1.241							
	3	1.218							
Standardized coefficients of final regression analysis		6.373	5.993	6.042	5.832	2.125	2.038	1.092	1.208
Standardized regression coefficient ranking		1	3	2	4	5	6	8	7
Mean value		0.217	1.133	0.093	0.001	0.01	0.174	0.054	0.061
Standard deviation		0.738	4.078	0.358	0.005	0.056	0.886	0.116	0.143
Final coefficient of multiple regression analysis		8.64	1.47	16.857	1071.774	37.809	2.301	9.381	8.424
Original variable regression coefficient ranking		5	8	3	1	2	7	4	6

prevailing. "model prevails. For example, 75% of the food and beverage waste in the village is plastic, which contrasts with the "biodegradable material substitution" path proposed by Chen et al. (Chen et al. 2024). Policy implications: It is recommended to implement a certification system for "low-carbon farmhouses", make the use of biodegradable tableware mandatory, and refer to the "low-carbon point system" of Li et al.(Li L et al., 2024), which links emissions reduction behaviors to business permits.

Road conditions limit motorcycle dominance with a shortage of charging piles. Due to the low penetration of private cars in rural areas, pedestrians mostly use battery cars and motorcycles to travel, so the carbon factors of both are larger than those of private cars. This indicates that the differences in the distribution of transportation facilities in the studied rural communities will seriously affect the corresponding carbon factors of transportation facilities, but it does not mean that the individual emissions of battery cars are necessarily larger than those of private cars, which are closely related to the road density and destination accessibility in rural communities (Jiang et al., 2021).C2 (motorcycle) has a weight of 66.168, reflecting the insufficient coverage of charging piles in rural areas, and the promotion of new energy vehicles (C3) is hindered. Meanwhile, the problems related to the density of village roads and destination accessibility within the village make the village roads unsuitable for automobile travel. However, motorcycles are more sustainable and economical than traveling with EVs, and villagers generally choose to purchase motorcycles for travel with higher willingness, forcing residents to rely on short-distance, high-carbon transportation (Jiang et al., 2021). It is suggested that the government should incorporate the construction of charging piles into the "village-to-village" project, and optimize the road network and the layout of new energy facilities by referring to the spatial planning model of Ao et al. (2023). At the same time, widening the roads and quality in the village can promote the promotion of new energy vehicles. Jiang et al. (2021) found that for every 10% increase in road density, the utilization rate of new energy vehicles increased by 8%, which is consistent with the findings of this study.

Table 9 Results of principal component analysis and multiple regression analysis of household transportation equipment carbon emissions.

		C1	C2	C3
Principal component	1	−0.095	0.993	0.075
	2	−0.16	0.073	0.984
	3	0.983	−0.092	−0.16
Initial eigenvalue	1	−0.1387	1.44978	0.1095
	2	−0.1384	0.063145	0.85116
	3	0.663525	−0.0621	−0.108
Principal component standardization coefficient	1	0.805		
	2	0.964		
	3	0.89		
Standardized coefficients of final regression analysis		0.381	0.804	0.784
Standardized regression coefficient ranking		3	1	2
Mean value		0.0682	0.0085	0.008
Standard deviation		0.0654	0.0122	0.0068
Final coefficient of multiple regression analysis		5.818	66.168	114.681
Original variable regression coefficient ranking		3	2	1

Fuelwood dependence and electricity consumption growth. Currently, rural areas in China are facing challenges such as energy structure transformation and environmental pollution caused by energy consumption, and the sustainable development of household energy is of great significance to rural residents (Sun et al., 2014). Despite the government's ban on open burning, D4 still tops the weights, reflecting insufficient penetration of clean energy sources (e.g., biogas). D1 (electricity) has a weight of 30.092, which is associated with rising household appliance penetration (e.g., air conditioner ownership increases by 35% by 2023), but a higher carbon intensity of the power grid (0.6 kg CO_2/kWh).

It is recommended that the government promote biomass pellet fuel as a substitute for traditional fuelwood and incorporate biogas digester construction into rural revitalization infrastructure projects, referring to the Ningxia case of He et al. (He et al., 2021). Xing et al. point out that rural energy transitions are constrained by income levels, while this study quantifies policy implementation fallout through the D4 coefficient (Xing et al., 2024).

Disconnect between landfill and incineration dominance and policy implementation: E2 (landfill) and E3 (incineration) account for 65% of carbon emissions, as the coverage of village-level sorting facilities is less than 10% (Liu et al., 2023). Although municipal waste classification regulations have been introduced, the lack of village-level supervision has led to the arbitrary

Table 10 Results of principal component analysis and multiple regression analysis of household energy equipment carbon emissions.

		D1	D2	D3	D4	D5
Principal component	1	0.021	−0.094	−0.031	0.956	0.957
	2	0.928	0.909	−0.103	−0.076	0.005
	3	−0.011	−0.138	0.993	−0.031	−0.009
Initial eigenvalue	1	0.04	−0.181	−0.06	1.842	1.844
	2	1.576	1.543	−0.175	−0.129	0.008
	3	−0.01	−0.128	0.918	−0.029	−0.008
Principal component standardization coefficient	1	1.304				
	2	1.275				
	3	0.885				
Standardized coefficients of final regression analysis		2.053	1.619	0.511	2.212	2.408
Standardized regression coefficient ranking		3	4	5	2	1
Mean value		0.07	0.017	0.001	0.00009	0.002
Standard deviation		0.068	0.011	0.003	0.001	0.015
Final coefficient of multiple regression analysis		30.092	153.067	159.501	4139.427	159.969
Original variable regression coefficient ranking		2	1	4	1	3

Table 11 Results of principal component analysis and multiple regression analysis of carbon emissions from domestic waste.

		E1	E2	E3
Principal component	1	0.105	0.929	0.879
	2	0.988	−0.019	0.251
Initial eigenvalue	1	0.186	1.649	1.56
	2	0.901	−0.017	0.229
Principal component standardization coefficient	1	1.436		
	2	1.278		
Standardized coefficients of final regression analysis		1.419	2.346	2.533
Standardized regression coefficient ranking		3	2	1
Mean value		0.004	0.015	0.014
Standard deviation		0.004	0.02	0.022
Final coefficient of multiple regression analysis		366.086	116.318	117.026
Original variable regression coefficient ranking		1	3	2

disposal of E1 (food waste), which villagers will dump directly into ridges or landfills, with methane emissions exceeding the standard value by 50%. It is recommended that the government improve the waste separation system, Liu et al. proved that separation facilities can reduce emissions by 12–18% (Liu et al., 2023). In the short term, a pilot program of "sorting and recycling station + straw return to field" should be implemented; in the medium term, it should be connected to the urban treatment system; and in the long term, legislation should be enacted for mandatory sorting (e.g., the Shanghai model, (Chen et al., 2020)).

Conclusion

In summary, this paper analyzes the carbon factors of rural communities, taking Xiange Village in Chengdu City as an example.

It was found that (1) from the five dimensions of the community, carbon emissions from the primary industry accounted for the highest proportion of total carbon emissions (64.21%), followed by the tertiary industry, household energy equipment, household transportation facilities and household food waste.

(2) The regression coefficients of carbon factors were studied from the perspective of 24 secondary indicators. The regression coefficients of the carbon factor of agricultural machinery (A5), the carbon factor of motorcycles (D4), the carbon factor of household food waste disposal (E1), the carbon factor of private cars (D3), and the carbon factor of household disposable goods (B4) are all greater than 100, so it is important to attach great importance to energy conservation and emission reduction in this part. At the community level, they have a great influence on carbon emissions.

(3) The carbon factors of each dimension are analyzed by principal component regression to derive the most important carbon factors of each dimension, which provides ideas for further research on the carbon factors of each dimension. To summarize, this paper combs the carbon emission inventory of rural communities and constructs the carbon factor evaluation system.

Therefore, three major conclusions are drawn:

(1) the structural causes of the dominance of agricultural carbon emissions: agricultural carbon emissions accounted for 64.21%, is due to high mechanization dependence and, fertilizer independent use of unreasonable. Citrus planting in diesel agricultural machinery (A5) carbon emission coefficient of 4547941.977, reflecting the "high input - high emission" mode. This phenomenon is directly related to the government's agricultural machinery subsidy policy, although the subsidy improves production efficiency, farmers still maintain a low level of efficiency in the use of machinery, and is not included in the assessment of carbon intensity (Tian et al., 2016). A3 (fertilizer use) and A4 (pesticide use) together contribute to 28.7% of the carbon emissions in agriculture, and the excessive inputs are due to the insufficient popularization of technology under the smallholder economy and the demand for short-term increase in production. The excessive inputs come from the lack of technology popularization and short-term yield increase under the smallholder economy. The government should incorporate carbon emission reduction targets into agricultural machinery subsidy standards, promote precision fertilizer application technologies (e.g., slow-release fertilizers), and incorporate carbon trading mechanisms to guide the low-carbon transition.

(2) High weighting of waste treatment (E) and governance challenges: The high weighting of carbon emissions from domestic waste, the lack of formal treatment modes in rural areas, and the absence of proper sorting facilities. Villagers arbitrarily landfill (E2) or incinerate (E3) waste, leading to a surge in CH_4 and CO_2 emissions (Chen et al., 2020). Meanwhile, the coverage of village-level recycling stations is insufficient and disconnected from the urban treatment system. It is recommended that the government should pilot the "recycling station + straw return to the field" in the short term, connect to the municipal waste incineration plant in the medium term, and legislate for mandatory waste separation in the long term.

(3) Rural-urban differences in transportation and energy equipment: motorcycles dominate transportation emissions and biomass energy is relied upon. c2 (motorcycles) has a weight of 66.168, far exceeding that of private cars ($c1 = 5.818$), reflecting the low coverage of charging piles in the countryside and the lag in the promotion of new energy vehicles. d4 (fuel wood) has a weight of 4,139.427, which is correlated with the low penetration of clean energy sources (e.g., biogas). It is recommended that government departments include the construction of charging piles in rural revitalization infrastructure planning and promote biomass pellet fuel to replace traditional fuelwood.

This study also has some limitations: (1) Carbon sinks were not quantified: citrus grove carbon sinks (about 0.8 t CO_2/mu-yr) were not accounted for, which may overestimate net agricultural emissions. (2) Sample regional limitation: the conclusion is based on a single case in Linpan, West Sichuan, and extension to other landscapes (e.g., mountain villages) needs to be verified. (3) Data timeliness: The questionnaire data are cross-sectional data from 2023, which fails to reflect dynamic changes.

In the future development, we can broaden the research scale, combine remote sensing technology to monitor the vegetation carbon sink dynamically, and construct the "emission-absorption" net value model. At the same time, regional comparisons can be strengthened to compare the differences in the weights of carbon factors among plains, mountains and coastal villages, so as to refine universal emission reduction strategies. Simulation can also be used for optimization, such as predicting the impact of policy interventions (e.g., carbon tax) on rural communities through Agent-Based Models.

Data availability

All data generated or analyzed during this study are obtained from field research conducted by team members between 20 April and 27 April 2023.The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request. Researchers who wish to access anonymized survey responses and should send a formal email to the corresponding author, accompanied by a statement of purpose.

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Author contributions
Yujie He provided the Abstract, Methods, Results, Discussion, and Conclusions sections; Pingjuan Zou provided the Introduction section; Lei Xu provided the Methods, Results, and Discussion section; Hang Chen provided the Methods section and Rui Peng provided the Methods and Discussion section. Correspondence to: Lili Zhang was responsible for the technical structure organization and thesis compilation, while Congshan Tian was responsible for the conceptualization, experimental design and practical arrangements. All authors read and approved the final manuscript.

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