Geographic networks matter for pro-environmental waste disposal behavior in Rural China: Bayesian estimation of a spatial probit model

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Abstract

Pro-environmental waste disposal behavior plays a fundamental role in improving rural waste management and rural livability. Recent years have witnessed an increased social, political and academic interest in the influencing mechanism of pro-environmental waste disposal behavior. In particular, it is widely acknowledged that social networks can influence the behavior of others via sharing information and opinions. However, given the theory of behavioral contagion, it is believed that geographic networks provide channels to directly observe the behavior of others and to further adapt self-behavior even in the absence of social networks. Despite this fact, a systematic analysis of how geographic networks affect waste disposal behavior is still lacking. Therefore, this study distinguishes the roles of geographic and social networks in shaping behavior and investigates the impact of geographic networks on four types of waste disposal behavior (i.e., domestic waste sorting, agricultural waste disposal, sewage collection, and toilet retrofitting) by Bayesian estimation of a spatial autoregressive probit model. The empirical results confirm that geographic networks affect four types of waste disposal behavior in a significantly positive way, while the positive impact of social networks is only detected in the case of sewage collection and toilet retrofitting. Besides, based on our dataset, the effect of geographic networks does not decrease as the distance between observations increases. Furthermore, taking spatial heterogeneity into account, different waste disposal behavior types respond differently to household background characteristics and local socio-economic conditions. These findings have significant implications for policymakers to design and develop sustainable waste management systems in rural China.

Keywords: Rural waste treatment; Waste disposal behavior; Geographic networks; Spatial interdependence; Spatial autoregressive probit model

JEL Classification: C11; C31; C83; D9; Q53

1. Introduction

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Rural decline has become a daunting global challenge, as the long-standing priority of urbanization and industrialization has inevitably overstretched capital, raw materials, labor and other resources (Liu and Li, 2017; Markey et al., 2008). Due to the lack of infrastructure and public services, rural decline is typically accompanied by severe rural waste management issues, which further deteriorate environmental pollution, threaten public health, and hinder rural economic growth (Põldnurk, 2015). Being the world's largest waste generator since 2004 (World Bank Group, 2005), China produced more than roughly 175 million tons of rural solid waste in 2017, of which at least 40% was dumped openly and burnt illegally (World Bank Group, 2019). Moreover, the generation rates of domestic waste ranged between 0.034 and 3.0 kg day^{-1} per capita in rural areas of China and have shown an accelerating trend (Han et al., 2019; Zeng et al., 2016).

In order to overcome these challenges, the nineteenth National Congress of the Communist Party of China proposed the Rural Vitalization Strategy (RVS) in 2017 to guide the rural development. Specifically, the "Three-year Action Plan for Rural Living Environment Improvement", implemented in 2018 as a leading strategy of the RVS, aiming at the construction of integrated sustainable waste disposal systems (The State Council of the People's Republic of China, 2018a). According to the details of this plan, major tasks and measures involve the overall modernization of domestic waste management, agricultural waste treatment, residential sewage processing, as well as toilet upgrades, but are not limited to these (The State Council of the People's Republic of China, 2018b). Theoretically, sorting at source is the ideal starting point of rural solid waste management, which could greatly ease the difficulties for subsequent waste treatment operations, improve waste treatment efficiency and benefit resource recycling (Wang and Hao, 2020). Regarding the wide variety of wastes generated from agricultural production, pesticide packaging (e.g., plastic bags and bottles) is considered a primary source of wastes. In fact, more than 100,000 tons of pesticide packaging are discarded improperly each year, resulting in large amounts of pesticide residues contaminating water and soil (Xu et al., 2021). Apart from these, considering that nearly 20 million tons of rural domestic sewage was discharged without proper treatment, it is also urgent to solve sewage treatment issues (Cheng et al., 2020). As an extension of the "China Toilet Revolution" national project, the toilet upgrade program in this plan seeks to further improve sanitation facilities and hygienic environment. According to statistics, by the end of 2020, the sanitary toilet coverage rate increased to 65% in rural areas (Zhang, 2020). Despite this progress in rural toilet retrofitting, over 17 million households are still exposed to poor hygiene situations (Cheng et al., 2018).

With the growing interest in rural waste management, a group of researchers has focused on analyzing household waste-related behavior and examining the impact of various socio-demographic and socio-psychological factors on waste management (Han et al., 2018; Massoud et al., 2009; Xu et al., 2021; Wang and Shen, 2022). The existing literature identifies the following issues and challenges. First, urban waste management has received more attention than rural waste management in the past decades due to rapid urbanization and urban population growth (Alhassan et al., 2020; Gu et al., 2017; Singh, 2019; Ye et al., 2020). Consequently, the waste-related research of urban areas has found essential results at both micro- and macro-level, while rural waste-related research has developed less dynamically, particularly at household level (Massoud et al., 2009; Wang et al., 2018; Zeng et al., 2015). Second, the lack of well-organized rural waste management services causes difficulties in collecting data on rural waste disposal, further impeding the progress of rural waste management research (World Bank Group, 2019; Zeng et al., 2015). Especially, large-scale assessments of waste disposal behavior in rural areas are still scarce due to the large amount of funding required for field surveys.

A closer look at the literature reveals that one branch of waste treatment research has emphasized the importance of social networks in the adoption and diffusion of sustainable waste treatment, but these studies are mostly limited to urban areas (Hua et al., 2021; Jones et al., 2010; Knickmeyer, 2020; Luo et al., 2020). Among these studies, social networks are usually built upon social relationships and shape waste disposal behavior by sharing information and opinions. Although the influence of geographic networks on behavior has also been recognized in some research, the distinction between the roles of geographic and social networks remains vague. For example, Abdul Mumin et al. (2022) treat geographic networks as one spatial dimension of social networks, while Corral and Radchenko (2017) consider social networks as a channel through which geographic networks can trigger neighborhood effects. Furthermore, the influence of geographic networks or similar concepts (e.g., spatial networks or connections) on waste disposal behavior has not been directly analyzed because coordinates information of study objects is generally unavailable.[1] At last, with broader application of Spatial Econometrics in various research fields, we believe that unveiling the role of geographic networks on waste treatment behavior could enrich the current understanding of the complexity of influencing mechanisms on waste disposal practices.

In view of the above, this study is devoted to answering the following research questions. First, what is the status quo of rural waste disposal performance at the household level in terms of domestic waste sorting, agricultural waste disposal, sewage collection, and toilet retrofitting? Second, this study defines geographic networks by distances among surveyed households to investigate the spatial interdependence of waste disposal behavior. Given this, one main objective of this research is to verify whether the pro-environmental waste disposal behavior of one household influences the behavior of others nearby. We further analyze how the impact of geographic networks on waste-related behavior varies when distance changes. At last, controlling for the influence of geographic networks, we examine how contextual factors influence different types of waste disposal behavior.

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[1] Some regional-level studies involving geographical factors do exist (Agovino et al., 2019; Paulauskaite-Taraseviciene et al., 2022; Wang et al., 2021), but these studies contribute less to the analysis of waste disposal behavior.

By addressing the research questions stated above, a number of contributions to the literature are made: (1) Referring to the multiple targets of the three-year action plan, our study integrates four types of waste disposal behavior (i.e., domestic waste sorting, agricultural waste disposal, sewage collection, and toilet retrofitting) and reveals the current situation and challenges of rural waste management. (2) Using data from a large-scale field survey ensures a more accurate picture of rural waste treatment and helps authorities make more scientifically-based waste management decisions. (3) The influence of geographic networks on waste disposal behavior is formally proposed and examined using spatial analysis, which provides a sound reference for the establishment of waste management communities and the enhancement of cooperation across rural areas.

The remainder of this article is structured as follows. In Section 2, we set forth the theoretical framework and derive detailed hypotheses. Section 3 presents the data collection and variables description. In Section 4, we briefly introduce spatial limited dependent variable models and describe model specification of a spatial probit model in the analysis of waste disposal behavior, as well as the associated estimation strategy. Section 5 includes empirical results, robustness tests, and a discussion of findings. The final section shows conclusions and policy implications.

2. Literature review and research hypotheses

2.1. *Theory of behavioral contagion, spatial law of geography and geographic networks*

One of the earliest papers defined behavioral contagion as the tendency of a recipient's behavior to align with an actor's behavior without the need for intentional communication (Polansky et al., 1950). In the decades to follow, the theory of behavioral contagion was further developed and delineated from previous psychological terms such as 'conformity', 'social facilitation', and 'imitation' through different prerequisites (e.g., the presence of obvious conflict and external incentives) (Wheeler, 1966). In this research, we stick to the original definition of behavioral contagion by Polansky et al. (1950), emphasizing the possibility of behavior spreading in the absence of social networks. More recent evidence shows that the improvement of environmental behavior depends not only on the information acquisition through social interactions but also on behavioral contagion (Zheng et al., 2019). Clearly, a pre-condition for behavioral contagion is the possibility of directly observing the behavior of others. We refer to this aspect as valid geographic networks in our study and measure these networks by distance among surveyed households.

Importantly, combining geographic networks with the First Law of Geography (Tobler, 1970), the interdependence of behavior strengthens as the distance between samples decreases. Keser et al. (2012), for example, reported that provinces sharing borders are more likely to have similar municipal waste generation rates. Such interdependence among neighboring regions as regards waste treatment were also revealed by Agovino et al. (2019) and Wang et al. (2021). In contrast, to further explore the interdependence of waste disposal behavior, we propose the following hypotheses:

Hypothesis 1: Geographic networks as defined by distance among households affect waste disposal behavior.

Hypothesis 2: The influence of geographic networks on waste disposal behavior diminishes as distance increases. This condition is required for the asymptotic normality assumption in Spatial Econometrics (Billé and Arbia, 2019).

2.2. Social networks and waste disposal behavior

Social networks are broadly defined as social interactions with family members, friends, colleagues, and other members with some degree of social closeness (Barnes et al., 2016). Theoretically, social networks emphasize access to information through verbal communication, even over great physical distances. In general, people who build more social connections with other members of society can get more information and advice, which, on the other hand, can influence their environmental behavior (Banerjee, 1992; Cho and Kang, 2017; Yang et al., 2020).

Numerous studies have investigated the impact of social networks on waste disposal behavior in various regions and countries and shown the importance of social networks when it comes to improving waste disposal behavior (Ghani et al., 2013; Hornik et al., 1995; Nguyen et al., 2015). More specifically, Zheng et al. (2020) use the number of relatives and friends to capture the strength of social networks and find a positive influence of social networks on participation in waste treatment. Besides, the frequency of social contact and the level of social closeness are used to study the relationship between social networks and individual waste-related behavior (Luo et al., 2020; Zheng et al., 2019). In addition, urban social network also plays a role in providing a positive environment (Corral and Radchenko, 2017; Dzanku, 2015). Building on these existing results about the role of social networks on waste disposal behavior, we formulate the following hypotheses:

Hypothesis 3: Dense social networks can improve waste disposal behavior significantly.

Hypothesis 4: Social networks with residents living in urban areas have a positive impact on the waste disposal behavior of rural residents due to the dissemination of up-to-date waste disposal information.

2.3. Motivation crowding theory, incentive measures and public participation

Early economic literature has demonstrated that inadequate technical and financial investments in waste treatment services in rural areas inhibit public participation in waste disposal (Li et al., 2019). In this context, incentive measures (e.g., monetary incentives), which can be regarded as effective environmental governance, play a critical role in encouraging public participation and accelerating the improvement of rural waste management. However, drawing upon the motivation crowding theory, the complexity of the influence of incentive measures has been revealed in the field of behavior economics. According to Frey and Jegen (2001), crowding theory involves a crowding-in effect and a crowding-out effect. This twofold impact questions the influence of any external intervention on public engagement and may cause undesired outcomes. Specifically, the crowding-in effect is associated with individuals' perceptions that positive intervention foster a supportive atmosphere, which further strengthens the intrinsic motivation and thus increase public participation. Conversely, the external intervention may mislead citizens to shift responsibility to local governments and reduce public participation, which is known as the crowding-out effect.

Rommel et al. (2015), for example, conclude that individuals who feel supported by incentives are more likely to engage in pro-environmental behavior. The incentives can also help improve waste separation by bridging the gap between intention and behavior (Wang et al., 2020). However, the crowding-out effect has been identified as well, especially in the environmental governance literature. Wang and Hao (2020) suggest that efforts from the central government decrease individual participation in waste sorting. Based on the uncertainty of the influence of governmental involvement and incentives, we propose the following hypothesis:

Hypothesis 5: Incentive measures, such as the provision of garbage collection facilities, technical guidance, and subsidies, can encourage the public engagement in sustainable waste disposal.

2.4. Social-demographic and psychological determinants of waste disposal behavior

Previous literature indicates that social-demographic factors, such as family size, income, and education, significantly affect waste disposal behavior (Li et al., 2019; Sorkun, 2018). Besides, accessibility of public services (e.g., accessibility of public transport or roads) could reflect the livability and remoteness of settlements, which further influence waste disposal behavior (Li et al., 2021). In terms of settlement density, Massoud et al. (2009) suggest that residents living in urban areas with a high population density perform better on centralized waste management systems than those living in rural villages with a low population density. Then again, it might be more difficult to motivate residents in high-population density communities to actively participate in sustainable waste disposal because they are likely to expect local governments to take more responsibility for sustainable waste treatment. What is more, understanding the role of psychological factors behind waste disposal behavior has received increasing attention. For instance, the perception of governance and the sense of communities have a profound impact on waste treatment activities (Cho and Kang, 2017; Varotto and Spagnolli, 2017). Accordingly, the following hypotheses are put forward:

Hypothesis 6: Family size, income, and education level are positively related to households' waste disposal performance.

Hypothesis 7: There is a positive correlation between accessibility of public services and waste disposal performance.

Hypothesis 8: High settlement density can undermine the public involvement on waste treatment activities.

Hypothesis 9: High evaluation about governance and communities encourages public participation in waste disposal.

3. Data source and variables description

3.1. Data source

The dataset used for this study is from the Survey on Ecological Conservation and High-Quality Rural Development in the Yellow River Basin conducted in 2020. It is based on stratified random sampling and includes 2,326 rural households in 182 villages from 13 counties in 6 provinces located in the Yellow River Basin. Due to the importance of the environment in the areas near the Yellow River, the selected villages and townships are located in close proximity to the Yellow River (see in Fig. 1). In order to comprehensively study sustainable development in rural areas, the survey contains more than 4 modules, including basic household information (e.g., family structure, education, housing type, social networks, etc.), agricultural production conditions, income and consumption, waste treatment, rural governance, and so forth. Importantly, the coordinates of respondents' residence are provided in this dataset. Following the research topic of this study, we focus on the modules dealing with waste management only and exclude all observations in the Qinghai province due to the high number of missing values there. The final number of observations is determined by the specific type of waste disposal behavior. It varies from more than 800 to 1,400 observations after removing observations with missing values and outliers.

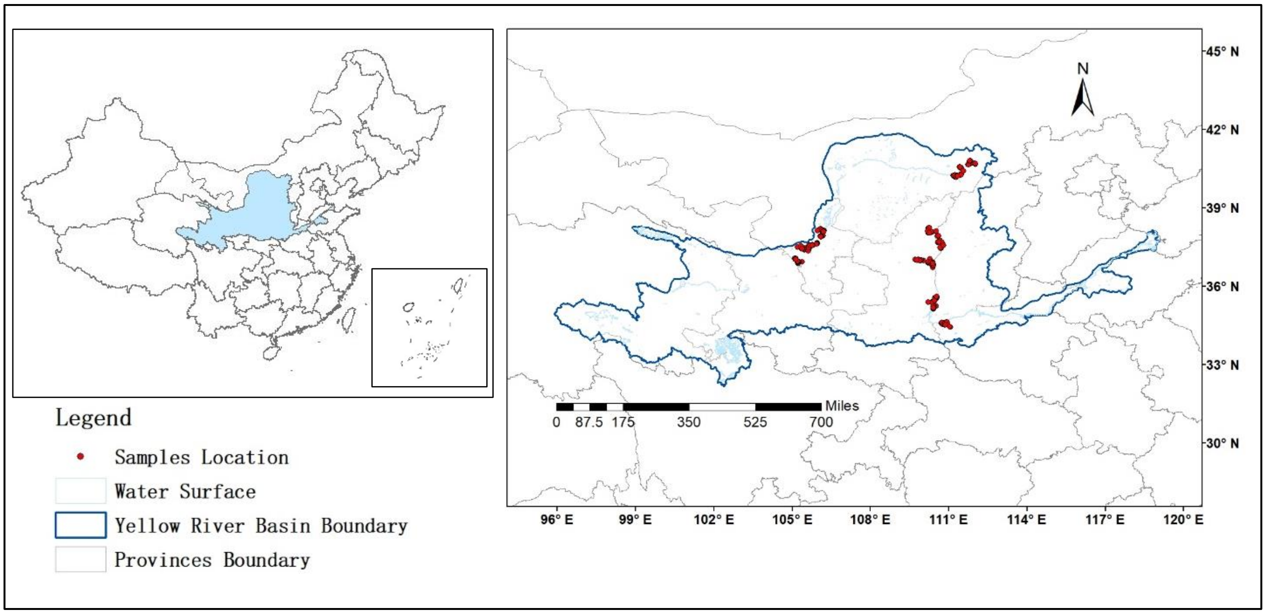


Fig.1. Samples distribution

3.2. Variables description

As mentioned in Section 1, the dependent variables used in this study consist of domestic waste sorting, agricultural waste disposal, domestic sewage collection, and toilet retrofitting. They were measured on the following scales. For the variable domestic waste sorting, the scale included the answer possibilities “no sorting”, “sorting of recyclable waste (e.g., papers, metals, plastic bottles, etc.) only”, “sorting of recyclable waste and organic kitchen waste”, and “sorting of recyclable waste, organic kitchen waste, and hazardous waste”, which were given values from 1 to 4. In this study, agricultural wastes refer to pesticide packaging (e.g., plastic bags and bottles used in agricultural production). Answers regarding agricultural waste disposal were classified into “dumping”, “landfill or incineration”, “selling to garbage collection center”, and “selling to agricultural waste collection points”. They were also given values from 1 to 4, respectively. As regards sewage collection, the answers were categorized into “dumping” and “doing sewage collection”. They received values of 0 and 1, respectively. The last dependent variable to be used, toilet retrofitting, refers to residents upgrading their toilets from simple dry toilets to flush toilets. It was linked to a simple “yes” or “no” question (i.e., “1” or “0”). The detailed statistical analyses of these four dependent variables will be presented in Section 5.1, showing readers a clearer picture of the current situation as concerns rural waste management in the sampling areas. To maintain consistency of measurement, dependent variables regarding domestic waste sorting and agricultural waste disposal are recoded as binary variables for the spatial binary probit model analysis. Meanwhile, using same model specification for all dependent variables improves the comparability and facilitates the interpretation of the results.

To examine hypotheses proposed in Section 2, we use the family population, education level of decision makers, and annual income per capita to investigate how family characteristics affect different types of waste disposal behavior. In terms of accessibility of public services, we employ the method named Technique for Order Preference by Similarity to an Ideal Solution (hereafter TOPSIS) to combine 7 distance-related indicators (i.e., distance to local government, distance to police station, distance to bank, distance to agricultural wholesale market, distance to stores for agricultural materials, distance to the nearest bus station, and distance to the nearest highway) into one composite indicator. And this composite indicator can reflect the overall accessibility, ranging from 0 to 1. The larger the value, the better the accessibility of public services. Similarly, the indicator representing the evaluation about governance and communities is generated by 7 relevant sub-indicators. These indicators measure the satisfaction levels of information disclosure, working ability of village cadres, village economic development, governance effectiveness, village regulations, village atmosphere, and the relationship between villagers, respectively. The related answers are measure on a 5-point Likert Scale. And the higher the value, the better the evaluation.

Apart from these, we use the number of close relatives and friends and the number of relatives and friends working in urban areas to represent social networks. The former indicates the scale of social networks, while the latter emphasizes the social interaction with new environmental protection information. The number of incentive measures is used to capture the strength of environmental governance, involving subsidies, provision of trash cans, establishment of garbage disposal center, technical guidance, and so forth. The original data about settlement density classification in 2020 is collected from Global Human Settlement Layer (https://ghsl.jrc.ec.europa.eu/ghs_smod2022.php) with a spatial solution of 1 km × 1 km (Schiavina et al., 2022). Combined with the GIS coordinates information of samples, the exact settlement density type for each household can be extracted in ArcGIS. The settlement density classification is valued from 1 to 7. Higher values indicate the higher settlement density.

For convenience, the explanatory variables description can be found in Table 1, Appendix 1, and Appendix 2. Additionally, in Fig. 1 the vector of the Chinese province administrative division is provided by the National Catalogue Service for Geographic Information (http://www.webmap.cn/). And the vector of the Yellow River Basin boundary is from the Resource and Environment Data Cloud Platform of the Chinese Academy of Sciences (http://www.resdc.cn/).

Table 1
Summary statistics of explanatory variables.

Explanatory Variables	Mean	Std. Dev.	Min	Max
Family size (person)	3.67	1.58	1.00	10.00
Education level (years)	7.15	3.59	0.00	16.00
Annual income per capita (10^4 yuan)	1.98	2.82	-1.47	47.78

Incentives	1.52	1.00	0.00	4.00
Accessibility of public services	0.01	0.04	0.00	1.00
Evaluation about governance and communities	0.68	0.13	0.13	1.00
Close relatives and friends (person)	6.32	6.93	0.00	35.00
Relatives and friends in urban areas (person)	2.65	3.67	0.00	28.00
Settlement density classification	2.82	1.41	1.00	7.00

4. Methodology

4.1. Spatial limited dependent variable models and identification

Based on the theory of behavioral contagion introduced in Section 2.1, one main purpose of this study is to do an in-depth assessment of the neighboring effects of waste disposal behavior among surveyed households. This can be pursued with the help of Spatial Econometrics. However, binary dependent variables used in this study rule out conventional linear spatial models and require the application of Spatial Econometrics in the field of discrete choices and limited dependent variables models.

To data, some techniques have been developed to model binary choice outcomes in a spatial structure. Generally, spatial binary dependent variable models refer to spatial binary probit/logit models, which have been extended into spatial multinomial probit/logit models, and spatial ordered probit/logit models, among others. Moreover, these spatial discrete choice models can be studied under different spatial settings (see Billé and Arbia, 2019 for a recent review), e.g., the spatial autoregressive probit model, the spatial error probit model, etc. In regards to computational technologies, maximum likelihood (ML) (Wang et al., 2013), generalized method of moments (GMM) (Pinkse and Slade, 1998), expectation maximization algorithm (ME algorithm) (McMillen, 1992), and their variants are commonly implemented to estimate spatially limited dependent variable models. The selection of estimation procedures largely depends on the specific methodological settings and targets and is generally linked to a trade-off between consistency and computational efficiency (Fleming, 2004).

In recent years, Bayesian Estimation with Markov Chain Monte Carlo (MCMC) has experienced rapid development in spatial limited dependent variable models because of its relative flexibility, computational efficiency (e.g., no numerical integration required by traditional Bayesian approach), and unbiased estimation of the standard errors (LeSage, 2000; LeSage and Pace, 2009). Regarding the improvement of Bayesian estimation of spatial limited dependent variable models in various research fields, see for example Abdul Mumin et al. (2022) on the diffusion of agricultural technology, Corral and Radchenko (2017) on income diversification, Krisztin et al. (2022) on land use change, LeSage et al. (2011) on business, Zeng et al. (2019) on freeway crash severity, and so forth. Nevertheless, only a few empirical studies have adopted Spatial Econometrics, particularly Bayesian estimation of a spatial probit model, to study the spatial dependence of waste disposal behavior. This methodological approach will be explained in the following sections.

4.2. Model Specification of the spatial binary probit model

Following LeSage and Pace (2009), the spatial autoregressive binary probit model (hereafter SAR probit model) takes the following form:

$$y^* = \rho W y^* + X\beta + \epsilon, \qquad \epsilon \sim N(0, \sigma_\epsilon^2 I_n) \tag{1}$$

where y^* indicates an $n \times 1$ vector reflecting the latent unobserved variable associated with binary waste disposal behavior y of the n households in our case. Specifically, y reflects four observed choice outcomes, which represent yes-no waste sorting, yes-no sewage collection, yes-no toilet retrofitting, proper-improper agricultural waste disposal, respectively. Similar to the conventional probit model specification, $y_i = 1, if\ y_i^* \geq 0$, while $y_i = 0, if\ y_i^* < 0$. Besides, y^* in the SAR probit model follows a truncated multivariate normal distribution (hereafter TMVN). The matrix X with parameters β is an $n \times k$ matrix of explanatory variables. Apart from these, it is assumed that the error term ϵ is an $n \times 1$ vector with zero mean and constant variance under normal distribution.

Importantly, the matrix W is an $n \times n$ spatial distance weight and captures geographic networks between observations. Based on the spatial information given by coordinates, the element w_{ij} is measured by the reciprocal of arc distances (unit: km) between household i and household $j \neq i$. Especially, the matrix W is built by row-normalization for subsequent analysis. The linear combination Wy^* indicates the spatial lag (also called spatial dependence) brought from neighboring observations. Additionally, the scaler ρ reflects the intensity of spatial lag and ranges from -1 to 1, where the model expressed in Eq. (1) collapses into a conventional probit model when $\rho = 0$.

Taking into account endogenous problems, the reduced form of Eq. (1) is given as follow:

$$y^* = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1}\epsilon = S(\rho)X\beta + S(\rho)\epsilon \tag{2}$$

And the related expectation is written as:

$$E(y = 1|X, W) = \Pr(y = 1|X, W) = F\{S(\rho)\, X\beta\} = F(\phi) \tag{3}$$

where I_n is an identity matrix of size n, and $(I_n - \rho W)^{-1}$ always exists for $|\rho| < 1$ when W is row-normalized. F(•) is a non-linear probability function with a function $S(\rho)X\beta$.

Given the nature of non-linearity and spatial dependence in the SAR probit model, the magnitude of estimated parameters $\hat{\beta}$ cannot directly reflect the change in the probability of $y = 1$ when an explanatory variable x_r changes by one unit. As discussed in LeSage and Pace (2009), the measurement of this non-linear relationship relies on the standard normal distribution, while the spatial dependence is determined by $(I_n - \mathrm{\rho W})^{-1}$. Accordingly, taking the explanatory variable x_r as an example, the $\mathrm{n} \times \mathrm{n}$ matrix of marginal effects at the mean $\bar{x}_r$ in the SAR probit model is expressed in (4), where $\phi(\bullet)$ is the standard normal density.

$$\frac{\partial \mathrm{E}(y = 1|x_r)}{\partial x_r'} = \phi(\mathrm{S}(\rho) I_n \bar{x}_r \beta_r) \odot \mathrm{S}(\rho) I_n \beta_r \tag{4}$$

Following the definition of marginal effects by LeSage and Pace (2009) and Lacombe and LeSage (2018), the diagonal elements (i.e., own-partial derivatives) in the matrix from Eq. (4) are labeled as direct effects, while off-diagonal elements (i.e., cross-partial derivatives) are viewed as indirect effects and measure spatial spillovers. The sum of direct effects and indirect effects is defined as total effects.

4.3. Estimation strategy of the spatial binary probit model

The Bayesian approach in conjunction with MCMC sampling aims to decompose the posterior distributions $\mathrm{p}(\beta|\rho, y^*)$ and $\mathrm{p}(\rho|\beta, y^*)$ into corresponding conditional distributions with prior distributions following Bayes' Rule. Similar to the conventional Bayesian SAR model discussed in Chapter 5 of LeSage and Pace (2009), we assume a normal prior $\mathrm{\beta \sim N(c, T)}$ with the mean c and variance T and can sample by expression (5).

$$\begin{gathered}\mathrm{p}(\beta|\rho, y^*) \propto \mathrm{N}(\mathrm{c}^*, \mathrm{T}^*) \\ \mathrm{c}^* = (X'\mathrm{X} + \mathrm{T}^{-1})^{-1}[X'(I_n - \mathrm{\rho W})y^* + T^{-1}c] \\ \mathrm{T}^* = (X'\mathrm{X} + \mathrm{T}^{-1})^{-1}\end{gathered} \tag{5}$$

A uniform prior for ρ is also assumed, which requires the expression (6).

$$\mathrm{p}(\rho|\beta, y^*) \propto |I_n - \mathrm{\rho W}| exp\left\{-\frac{1}{2}[(I_n - \mathrm{\rho W})y^* - X\beta]'[(I_n - \mathrm{\rho W})y^* - X\beta]\right\} \tag{6}$$

As already noted, the latent unobserved dependent variable y^* follows TMVN (seen in expression (7)) and is treated as a set of parameters needed to be estimated.

$$\begin{gathered}y^* \sim TMVN\{(I_n - \mathrm{\rho W})^{-1}X\beta, [(I_n - \mathrm{\rho W})'(I_n - \mathrm{\rho W})^{-1}]\} \\ y^* \sim TMVN(\mu, \Omega)\end{gathered} \tag{7}$$

In the work of Albert and Chib (1993), sampling each value of y^* from its conditional contribution first could simplify the sampling process for remaining parameters β and $\mathrm{\rho}$, as in the case of spatial models with continuous dependent variables. One of the most best-known approach to sample y^* from TMVN is the m-step Gibbs sampling proposed by Geweke (1991). A major advantage of this approach is that the sampling process of y^* from TMVN is equivalently transformed into a sampling process from a normal distribution, which can efficiently generate y^*. Considering the existing literature (Bivand et al., 2021; LeSage and Pace, 2009; Wilhelm and de Matos, 2013) and the number of samples, our research is based on 1,500 draws with the omission of the first 300 draws and $\mathrm{m} = 10$. The setting-up of 10,000 draws is also used for the convergence check.

5. Results and discussion

5.1. Statistical analysis of waste disposal behavior

This section aims to shed light on the current situation and challenges of rural waste treatment using descriptive statistics. In terms of domestic waste disposal, more than 92% of all households indicated that they are willing to do waste sorting. However, around 34% of the studied households do not sort their domestic waste at all, which means there is a certain discrepancy between willingness and actual waste sorting behavior. Furthermore, about 63% of the households perform simple waste sorting, while less than 3% carry out detailed separation. For subsequent analyses, the answers “sorting of recyclable waste (e.g., papers, metal, plastic bottles, etc.) only”, “sorting of recyclable waste and kitchen waste”, and “sorting of recyclable waste, kitchen waste, and hazardous waste” are combined into one category, which is given a value of 1. Correspondingly, the answer “no sorting” is coded with 0. This binary dependent variable will be used in the Bayesian estimation.

As regards agricultural waste disposal, around 41% of all households are willing to dispose of their agricultural waste in an environmentally friendly way, but at the same time indicate improper disposal behavior. Specifically, around 19% dump agricultural waste causally and nearly 23% dispose of their agricultural waste via incineration or landfill. It needs to be stated that the damage to the environment resulting from waste treatment operations “dumping” and “incineration or landfill” cannot be measured and compared strictly on the basis of our study. Therefore, these two disposal measures are merged into one (improper) agricultural waste disposal category receiving a value of 0. In contrast, 58% of all households apply relatively proper agricultural waste disposal measures (coded with 1). Concerning the last two types of waste disposal behavior, around 37% of all households dump their domestic sewage improperly, and more than 55% still use pit toilets.

5.2. Spatial interdependence of waste disposal behavior

As described in Section 4.2, spatial distance weights are built by the inverse of arc distances between observations, emphasizing that close neighbors share higher spatial weights. These spatial distance weights define the intensity of geographic networks, which in turn are hypothesized to affect waste disposal behavior. In the model analyses, default arc distances are set as distance threshold bandwidths to construct spatial distance weights for the four types of waste disposal behavior. Besides, default distance bandwidths allow each sample to participate in the spatial analysis, meaning that all samples could build a geographic network with at least one neighboring sample. The advantage of this setup is that the sample information can be fully exploited (see more details in Getis (2009)).[2]

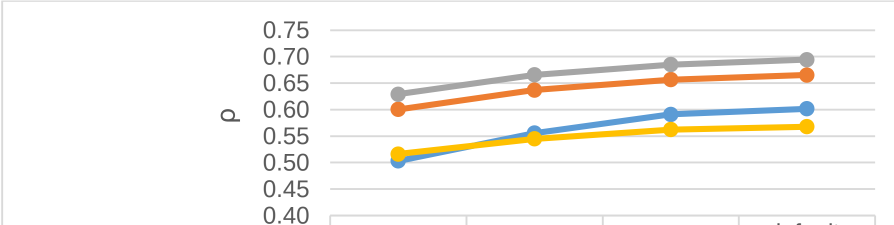
It is worth clarifying that an observation cannot be identified as the neighbor of another observation when the distance between them is beyond the distance threshold bandwidth. Due to the different sample sizes for the different types of waste disposal behavior used in our study, the default distance bandwidths vary. Specifically, the default distance threshold bandwidth for agricultural waste disposal is 17 km, which indicates that observations are not considered as neighbors of each other if the distance between them exceeds 17 km. For the remaining three dependent variables, the default distance is 13 km. In order to further investigate how the intensity of spatial dependence changes when the distance threshold varies, the SAR probit model is estimated at smaller distance threshold bandwidths of 1 km, 5 km, and 10 km, respectively. The estimates obtained from this step will also be used for robustness tests described in Section 5.4. It is important to bear in mind that a certain number of observations lose their neighbors when the distance threshold bandwidth is narrowed. The spatial interdependence of waste disposal behavior then ignores the influence of relatively distant neighbors and only highlights the waste disposal behavior of very close neighbors.

Fig. 2 shows all estimates as regards the intensity of spatial dependence (i.e., ρ) under four different distance bandwidths for different types of waste disposal behavior. It is essential to mention that all estimates of ρ for four types of waste disposal behavior are positive and statistically significant at the 1% level. This points towards a positive impact of geographic networks on the probability of proper waste disposal, which further supports Hypothesis 1. These results negate the independence of waste disposal behavior among neighboring observations and suggest that geographic networks should be considered when studying household waste disposal behavior.

Furthermore, the top half of Figure 2 illustrates that the strength of the spatial dependence varies under different distance bandwidths. Recall that more relatively distant neighbors are involved in the spatial analysis at larger distance bandwidth. In this context, the strength of spatial dependence is supposed to decrease as comparatively close neighbors are assigned smaller weights after row-normalization of the spatial weights. Contrary to this expectation, the spatial dependence for the four types of waste disposal behavior increases with increasing distance bandwidth, which lets us reject Hypothesis 2. It can be expected that the strength of spatial dependence follows an inverse U-shape if the sample size and distance

[2] In contrast to the k-nearest contiguity weight matrix (Corral and Radchenko, 2017), the distance weight matrix can provide extra distance information when authorities design the scope of policy implementation.

bandwidth are large enough. If so, the vertex generated by the inverse U-shape would show us at which distance the impact of geographic networks diminishes.



	1 km	5 km	10 km	default distance
Waste sorting	0.503	0.556	0.591	0.602
Agricutual waste disposal	0.600	0.637	0.656	0.665
Sewage collection	0.629	0.666	0.685	0.694
Toilet retrofitting	0.516	0.545	0.562	0.568

Fig. 2. Estimates about the intensity of spatial dependence

5.3. Impact of explanatory variables on waste disposal behavior

5.3.1. Parameter estimation of explanatory variables

As mentioned in the previous section, the intensity of spatial dependence varies for different types of waste disposal behavior. Thus, various explanatory variables are likely to have different effects on different types of waste disposal behavior. For statistically significant explanatory variables, the signs of their estimated coefficients $\hat{\beta}$ accord with the signs of marginal effects and can be used to interpret the influence of explanatory variables (Lacombe and LeSage, 2018). As such, Table 2 shows coefficient estimates and provides a preliminary indication of which explanatory variables have a significant influence on waste disposal behavior. Yet, the magnitude of the estimated coefficients $\hat{\beta}$ cannot be interpreted as the probabilistic impact of explanatory variables on dependent variables in the SAR probit model. For this reason, the analysis of marginal effects is further discussed in the next section.

What stands out in Table 2 is that different waste disposal behavior types are influenced to varying degrees by the explanatory variables. Firstly, family size and education level only significantly and positively affect the probability of domestic waste sorting. This result suggests that larger families, which tend to generate more domestic waste, see the necessity of waste sorting and can profit from cost-efficiency when doing it. Furthermore, people with higher education levels are more likely to have environmental awareness, which can contribute to better waste sorting behavior. Besides, higher annual income drives an increased probability of performing well in agricultural waste disposal, sewage collection, and toilet retrofitting, but not in waste sorting. One possible explanation is that improvements in sewage collection and toilet retrofitting require more financial investments in associated equipment. All of these results confirm the validity of Hypothesis 6.

Our results further suggest that incentive measures significantly increase the probability of public participation in sewage collection and toilet retrofitting, meaning that the crowding-in effect from environmental governance motivates people to engage in sustainable waste management and also alleviates the financial pressure to upgrade the equipment. This argument is consistent with the theoretical expectation put forward in Hypothesis 5. In terms of Hypothesis 7, all four types of waste disposal behavior appear to be unaffected by the accessibility of public services. Surprisingly, a higher appreciation of governance and communities leads to a significant decrease in the probability of waste sorting, which violates Hypothesis 9. Wang and Hao (2020) reported similar findings that high evaluation about governance can undermine public participation in waste sorting because high evaluation may mislead people to shift responsibility in waste management to institutions and communities and to expect more environmental governance. To overcome this issue, it is crucial to emphasize that citizens are also stakeholders and share the responsibility for improving waste management.

Importantly, consistent with Hypothesis 3, stronger social networks (as measured by the number of close relatives and friends) increase the probability of sewage collection and toilet retrofitting, while this is not the case for domestic waste sorting and agricultural waste disposal. As concerns Hypothesis 4, the results fail to prove it because we did not detect a positive influence of urban social networks on waste disposal behavior via sharing updated waste management information. In addition, a negative influence of high settlement density on sewage collection and toilet retrofitting was found, which supports Hypothesis 9. One reasonable explanation is that people living in densely populated areas depend to some extent on centralized waste management systems rather than investing themselves in decentralized waste management, especially for costly waste disposal practices.

Table 2
Coefficient estimates for parameters in SAR probit model

	Waste sorting		Agricultural waste disposal		Sewage collection		Toilet retrofitting	
Explanatory variables	Coef.	Std. Dev	Coef.	Std. Dev	Coef.	Std. Dev	Coef.	Std. Dev
Family size	0.081**	0.027	0.001	0.030	0.034	0.025	0.001	0.023
Education level	0.024*	0.012	-0.016	0.013	-0.008	0.010	-0.002	0.010

Annual income per capita	-0.004	0.017	0.039·	0.021	0.036*	0.016	0.040**	0.014
Incentives	0.029	0.040	0.045	0.043	0.085*	0.037	0.064·	0.034
Accessibility of public services	0.062	1.985	1.663	1.449	1.386	1.153	-0.675	0.773
Evaluation about governance	-0.444*	0.195	0.087	0.233	-0.096	0.180	-0.152	0.164
Close relatives and friends	-0.007	0.006	0.007	0.007	0.017**	0.006	0.014**	0.005
Relatives and friends in urban areas	0.015	0.011	-0.018	0.013	0.011	0.010	-0.002	0.009
Settlement density	0.004	0.026	-0.009	0.029	-0.072**	0.022	-0.058**	0.022

Note: *** = $\Pr(>|z|) < 0.001$, ** = $\Pr(>|z|) < 0.01$, * = $\Pr(>|z|) < 0.05$, · = $\Pr(>|z|) < 0.1$.

5.3.2. Marginal effects of explanatory variables on waste disposal behavior

Following Lacombe and LeSage (2018), direct effects in this study refer to the probabilistic impact of a change in one certain explanatory variable for household i on its own waste disposal choices, while indirect effects measure how waste disposal choices of household i change given one unit change of an explanatory variable of household j. One point to note is that the estimated intervals of direct/indirect effects of insignificant explanatory variables span zero, thereby losing the necessity of providing further statistical explanation. Marginal effects of statistically significant explanatory variables are shown in Table 3 without specifying total effects, which can be obtained by summing up direct effects and indirect effects.

In terms of domestic waste sorting, changes in family size and education level for a typical household i have mean positive direct effects of 2.9% and 0.9 %, respectively, while the corresponding average indirect effects are 3.9% and 1.2% respectively. Furthermore, how respondents evaluate the performance of governance and communities has the negative direct effect with a magnitude of 15.9% and the negative indirect effect with a magnitude of 21.3%. As to agricultural waste disposal, the average direct effect of annual income per capita was estimated to reach 1.6%, which is smaller than the indirect effect of 2.7%. Responses for sewage collection and toilet retrofitting to explanatory variables (incl. annual income per capita, incentives, close relatives and friends, and settlement density) are all statistically significant and go in the same direction, but with different magnitudes. More importantly, it should be noted that the range for indirect effects in lower 0.05 and in upper 0.95 credible intervals reflects that individual spillovers matter and vary substantially.

Table 3

Marginal effects estimation of SAR probit model

Explanatory variables	Direct effects	Indirect effects

	Lower 0.05	Mean	Upper 0.95	Lower 0.05	Mean	Upper 0.95
For domestic waste sorting						
Family size	0.014	0.029	0.045	0.018	0.039	0.064
Education level	0.002	0.009	0.016	0.002	0.012	0.022
Evaluation about governance	-0.274	-0.159	-0.044	-0.391	-0.213	-0.056
For agricultural waste disposal						
Annual income per capita	0.002	0.016	0.030	0.004	0.027	0.053
For sewage collection						
Annual income per capita	0.004	0.013	0.023	0.008	0.026	0.044
Incentives	0.008	0.031	0.052	0.015	0.060	0.103
Close relatives and friends	0.003	0.006	0.010	0.005	0.012	0.019
Settlement density	-0.038	-0.026	-0.013	-0.076	-0.050	-0.026
For toilet retrofitting						
Annual income per capita	0.007	0.016	0.025	0.008	0.019	0.032
Incentives	0.003	0.026	0.048	0.004	0.031	0.061
Close relatives and friends	0.002	0.006	0.009	0.003	0.007	0.012
Settlement density	-0.037	-0.023	-0.009	-0.048	-0.028	-0.011

5.4. Robustness test

To verify Hypothesis 2, different distance threshold bandwidths can be used to test whether the impact of geographic networks on waste disposal behavior dies when distance threshold bandwidth increases. On the other hand, distance threshold values also determine the sample size in model analysis. In general, larger distance bandwidths can loosen the requirement for the construct of geographic networks and involve more samples for spatial analysis. Thereby, the robustness test for the SAR probit model in this study is to see how sensitive our estimates and inferences are to the choice of distance bandwidths (i.e., 1 km, 5 km, 10 km and default bandwidth). Table 4 compares the estimates and inferences at different distance bandwidths for four types of waste disposal behavior. For clarity, we only retain explanatory variables that have statistically significant impacts on waste disposal behavior in Table 4. Compared to coefficient estimates in Table 2, it can be easily concluded that the effect of explanatory variables on four types of waste disposal behavior does not change significantly when distance bandwidth increases, especially for agricultural waste disposal and toilet retrofitting. Furthermore, under a distance bandwidth of 5 km, people having more urban social networks (as measured by the number of relatives and friends working in the city) are more likely to have the latest knowledge on waste sorting, which further increase the probability of waste sorting. In summary, we believe that the results from the SAR probit model are robust.

Table 4

Estimates under different distance bandwidths for four types of waste disposal behavior

	1 km	5 km	10 km	default distance

Explanatory variables	Coef.	Signif.	Coef.	Signif.	Coef.	Signif.	Coef.	Signif.
For waste sorting								
Family size	0.098	***	0.087	**	0.082	**	0.081	**
Education level	0.023	*	0.025	*	0.024	*	0.024	*
Evaluation about governance	-0.498	*	-0.513	**	-0.481	*	-0.444	*
Friends in urban areas	0.017		0.018	·	0.015		0.015	
For agricultural waste disposal								
Annual income per capita	0.043	*	0.040	*	0.041	*	0.039	·
For sewage collection								
Family size	0.056	*	0.039		0.036		0.034	
Annual income per capita	0.038	**	0.037	*	0.037	*	0.036	*
Incentives	0.063	·	0.077	*	0.086	*	0.085	*
Close relatives and friends	0.017	**	0.017	**	0.017	**	0.017	**
Settlement density	-0.070	**	-0.070	**	-0.070	**	-0.072	**
For toilet retrofitting								
Annual income per capita	0.040	**	0.040	**	0.041	**	0.040	**
Incentives	0.052		0.069	·	0.067	·	0.064	·
Close relatives and friends	0.013	*	0.015	**	0.015	**	0.014	**
Settlement density	-0.051	*	-0.056	**	-0.056	*	-0.058	**

Note: *** = $\Pr(>|z|) < 0.001$, ** = $\Pr(>|z|) < 0.01$, * = $\Pr(>|z|) < 0.05$, · = $\Pr(>|z|) < 0.1$.

6. Conclusions and policy implications

Based on household-level survey data, this study explicitly distinguishes the concept of geographic networks from that of social networks and originally provides evidence for the importance of taking geographic networks into account when studying waste disposal behavior. Our study uses Bayesian estimation of a SAR probit model to efficiently address nonlinearity and spatial heterogeneity arising from the model specification and clearly demonstrates how geographic networks affect different types of waste disposal behavior at a given distance bandwidth. Moreover, household characteristics and local socio-economic conditions are integrated in the spatial analysis to better understand the influencing mechanisms behind waste disposal behavior.

The main findings are as follows. Firstly, unlike studies that are limited to one type of waste disposal behavior, this study considers four fundamental types of waste disposal behavior (i.e., domestic waste sorting, agricultural waste disposal, sewage collection, and toilet retrofitting) to comprehensively assess rural waste management performance. Specifically, more than one-third of the studied households do not separate domestic waste or collect domestic sewage, nor do they dispose of agricultural waste properly. At the same time, more than half of the households do not replace dry toilets with flush toilets. These findings highlight the challenges of implementing the “Three-year Action Plan for Rural Living Environment Improvement”. Secondly, in light of the theory of behavioral contagion, this study emphasizes the difference between geographic networks and social networks and objectively reveals the positive impact of geographic networks on improving waste disposal behavior. Consistent with previous literature, it is proved that social networks can also play a positive role in waste management through peer effects. In terms of household characteristics, the positive effects of family size, education level, and income are identified and varies across the four types of waste disposal behavior. As for socio-economic conditions, this study confirms that incentive measures for waste management promote sustainable waste management. Another important finding is that highly appreciating governance and high settlement density may cause people to anticipate centralized waste management systems and take less responsibility for environmental protection, which further inhibits public participation in better waste management practices.

Together these results provide important insights for policymakers. Firstly, given the importance of geographic networks, policymakers need to recognize the power of behavioral contagion, which can further encourage them to improve household waste management by setting good examples of waste disposal behavior within neighborhoods, strengthening the functioning of communities, as well as collaborating across regions. Secondly, it is critical to enhance self-regulation and citizen engagement in waste management through providing relevant information and knowledge, investing in education, and publicizing the importance of individual responsibility in environmental protection. Especially, promoting awareness for public participation in waste management is essential to avoid motivation crowding-out effect when authorities design and implement incentive measures. Meanwhile, the relatively low settlement density in rural areas requires local authorities to adopt decentralized waste management systems rather than centralized ones. Apart from these, both sewage collection and toilet retrofitting are capital-intensive waste treatment operations, which gives rise to similarities in their influencing mechanisms. This finding can inspire policymakers to create synergies between waste management systems, thus improving waste management efficiently.

Several limitations and issues need to be acknowledged and further addressed in future research. Firstly, while the impact of geographic networks is predicted to increase first and then diminish when distance bandwidth increases, the current dataset did not allow to examine this claim. Besides, due to the unique feature of agricultural waste, this study can only provide limited information to explain how basic household characteristics and socio-economic conditions affect agricultural waste disposal behavior. Further research on the influencing mechanism of agricultural waste disposal behavior requires additional predictors about agricultural production.

Credit author statement

Xiaojie Wen: Writing – original draft, Revision. Philipp Mennig: Revision, Supervision. Hua Li: Data curation. Johannes Sauer: Supervision.

Declaration of Competing Interest

None.

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Appendix 1. Descriptive statistics of distance-related sub-indicators. (Unit: km)

Variables	Mean	Std. Dev.	Min	Max
Distance to local government	10.83	7.67	0.01	35.00
Distance to police station	9.51	7.48	0.01	36.00
Distance to bank	8.34	7.38	0.01	40.00
Distance to agricultural wholesale market	10.23	8.60	0.01	45.00
Distance to stores for agricultural materials	7.04	7.23	0.01	40.00
Distance to the nearest bus station	6.21	6.67	0.01	35.00
Distance to the nearest highway	5.58	7.07	0.01	35.00

Appendix 2. Descriptive statistics of sub-indicators regarding evaluation about governance and communities. (Measurement: 5-point Likert Scale)

Variables	Mean	Std. Dev.	Min	Max
Information disclosure	3.58	0.98	1.00	5.00
Working ability of village cadres	3.83	0.89	1.00	5.00
Village economic development	3.27	0.98	1.00	5.00
Governance effectiveness	3.78	0.89	1.00	5.00
Village regulations	3.76	0.80	1.00	5.00
Village atmosphere	4.19	0.75	1.00	5.00
Relationship between villagers	4.31	0.68	1.00	5.00

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