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To Achieve Carbon Neutrality, What Do Individual Residents Say? A Case Study of Yunnan Province of China Based on Spatial Analysis

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Abstract

This study aims to explore factors that affect individual residents' behaviors contributing to reducing carbon emissions (low-carbon behaviors), based on the empirical analysis of the choice of adoption and the extent of adoption of low-carbon practices, such as using low-carbon transportation and energy-saving, in Kunming, China. We use spatial econometric regression models to consider positive spillover of low-carbon behaviors amongst residents as people tend to obtain knowledge and learn good actions from those located nearby. The results show the existence of positive spillover effects of low-carbon behaviors across several types of low-carbon practices. We find that location effects, such as access to parks, residents' knowledge of carbon neutrality, and science communications in the local community are the most important determinants of residents' low-carbon behaviors. The findings may provide insights into designing supporting policies to incentivize residents' low-carbon behaviors and contribute to the pathway toward carbon neutrality from the micro-perspective.

Plain language summary

This study aims to explore factors that affect individual residents' behaviors contributing to reducing carbon emissions (low-carbon behaviors), based on the empirical analysis of the choice of adoption and the extent of adoption of low-carbon practices, such as using low-carbon transportation and energy-saving, in Kunming, China. By using a spatial analysis method, the study finds that spatial dependence exists in residents' low-carbon behaviors; knowledge and science communications are the key determinants of residents' adoption and extent of adoption of low-carbon practices; and location effects, such as access to parks and waterways, have a positive impact on residents' adoption and extent of adoption of low-carbon practices. The findings provide actionable insights into the low-carbon behaviors of residents in China, it should be of strong interest to policymakers that aim to facilitate low-carbon behaviors to achieve the net-zero goal by 2060 in China. Due to the data limitation (only based on one city in China), further research on low-carbon behaviors may consider expanding the sample size to include more cities and regions and testing for the spatial effects as well as the impacts of the key factors identified in this study.

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Data Availability Statement included at the end of the article

Keywords
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Introduction

Global coalition for carbon neutrality by 2050 is the most urgent goal to deal with the risk of catastrophic climate change. Up till now, the biggest polluters—the United States (US), the European Union (EU), and China—covering about 76% of global emissions, have set a net-zero target (United Nations, n.d.). Furthermore, the EU, Japan, and the Republic of Korea, together with more than 110 other countries, have pledged carbon neutrality by 2050 (Guterres, 2020). China, the largest developing economy, has committed to reaching the carbon peak by 2030 and achieving carbon neutrality before 2060 (Dong et al., 2022). However, China faces significant challenges in the progress of transiting toward carbon neutrality mainly due to its low energy utilization efficiency and shorter transition time frame (Zhao et al., 2022). Currently, China's energy consumption and carbon dioxide emissions continue to rise and its carbon peak is to be reached by 2030. Hence, the transition time for China's carbon peak to the goal of net-zero is shorter than that of the developed countries. Meanwhile, China's energy consumption is highly dependent on traditional fossil energy with a low energy utilization efficiency (Zhao et al., 2022).

Therefore, to achieve the net-zero goal, the coalition of governments, cities, businesses, and residents is pledging to leverage all sorts of efforts and resources, including both the macro- (e.g., policy and national level) and micro-level contributions (e.g., individual residents; Khan et al., 2022). Although there has been an extensive discussion of carbon neutrality in the literature and practice, the research in China has mainly focused on the macro-level impact analysis of carbon reduction policies. One strand of literature focuses on estimating the impact of policies and divergent pathways regarding resources, risk, and economic cost toward carbon neutrality (X. Chen & Lin, 2021; Zhang et al., 2021); the other strand looks into the regional or industrial level impact assessments, where the results provide the evidence of the economic, social and environmental benefit of reducing carbon emissions, and importantly, address the industrial- and regional differences in policy design (Dong et al., 2022; Khan et al., 2022; Xie et al., 2021; Yu et al., 2017; Zhang et al., 2021).

However, policymakers should focus not only on regional or industrial sources of emissions but also on individual households (Vandenbergh & Steinemann, 2007). As revealed by a study in the US, individuals take up more than 30% of carbon emissions in the US (Vandenbergh & Steinemann, 2007). Similarly, household consumption is one of the leading drivers of carbon emissions in China (Cao et al., 2018)—a 1% increase in household consumption leads to an increase in carbon emissions by 0.31% to 0.46% in the long run (J. Liu et al., 2021). Given the significant contribution of household consumption to carbon emissions, it is important to understand individual household's or resident's low-carbon behavior or behavior change. For instance, the change from fossil-based energy consumption to renewable energy consumption is expected to curb carbon emissions (J. Liu et al., 2021). Thus, understanding what drives people's low-carbon behaviors is crucial to achieving carbon neutrality.

Till now, to our best knowledge, no study has attempted to examine individual residents' adoption of low-carbon practices, with the consideration of people's spatial interactions. The existing studies based on qualitative research methods tend to provide conceptual models for understanding people's low-carbon behaviors (Moloney et al., 2010). For instance, some studies focus on the psychological aspect of people's responses to climate change (Clayton, 2020) and the effectiveness of communication of climate change to the public by assessing community-based programs and initiatives (e.g., Armstrong et al., 2018; Schäfer et al., 2018). Other studies intend to explore one specific low-carbon practice, such as a home management system (X. Liu & Jin, 2019), household heat decarbonization (Sovacool et al., 2021), and travel-related behaviors (J. Wu et al., 2023), or households' low-carbon consumption behaviors (Axsen & Kurani, 2012; Ding et al., 2018; T. Wang et al., 2021). There are only a few studies, such as W. Chen and Li (2019) that look into a variety of low-carbon behaviors and investigate factors that affect the adoption of low-carbon behaviors. However, none of the studies consider the extent of adoption (i.e., the number of low-carbon practices adopted) or the impact of spatial effects on the adoption of low-carbon behaviors.

Inspired by the above facts, this study aims to empirically explore factors affecting low-carbon behaviors concerning residents' adoption and the extent of adoption of low-carbon practices. The study contributes to the literature on carbon-neutral individuals and low-carbon behaviors in two ways. First, being the first attempt that considers individuals' spatial interactions, it provides empirical evidence of the status quo of individual residents' low-carbon behaviors that contribute to achieving carbon neutrality, based on the case of Kunming, China. The findings highlight the importance of considering individual efforts in designing the pathway toward carbon neutrality. Second, it addresses the factors that affect residents' adoption of low-carbon practices as well as the extent of adoption (measured as the number of low-carbon practices adopted), which fill in the gap of understanding residents' low-carbon behaviors concerning both binary decision-making (i.e., adopt or not adopt) and the extent of adopting good practices. As the findings provide actionable insights into the low-carbon behaviors of residents in China, it should be of strong interest to policymakers that aim to facilitate low-carbon behaviors to achieve the net-zero goal by 2060 in China.

The remainder of the paper is organized as follows. Section "Literature Review" describes the research methods and sample data used in the empirical analysis, followed by Section "Methods and Data" to present the results and discussion. The conclusion is made in the last section.

Literature Review

Adoption of low-carbon practices by individuals or households is a critical factor in mitigating climate change and transitioning towards a sustainable future. The literature on adoption analysis shows that individuals' adoption of pro-environmental practices (PEs) is contingent on many factors that can be categorized into four broader groups namely, (1) individual or household characteristics (e.g., demographic information) (e.g., Sovacool et al., 2021; Vandenbergh & Steinemann, 2007; T. Wang et al., 2021), (2) social and cultural norms (e.g., Axsen & Kurani, 2012; Thøgersen, 2006), (3) availability of support and resources, such as financial incentives, policies, and accessibility to infrastructure (e.g., Armstrong et al., 2018; Moloney et al., 2010; Schäfer et al., 2018), and (4) psychological factors, such as perceptions of and attitudes toward sustainability and the environment (e.g., Bockarjova & Steg, 2014; Clayton, 2020). Hence, the existing literature on the adoption of PEs provides insights into a number of determinants that should be considered in the empirical analysis. It is important to note that the relative importance of these factors may vary across contexts and individuals (Ding et al., 2018; Sovacool et al., 2021; T. Wang et al., 2021).

Two streams of studies have a specific focus on low-carbon behaviors. The first stream intends to understand factors affecting the adoption of one type of low-carbon practice or one group of people. For example, the home management system is usually seen as one of the most relevant ways for households to transform from a conventional energy system to a new one with a low-carbon focus (X. Liu & Jin, 2019). Another example is households' decision-making on the means of home-heating which is closely related to energy use and energy use efficiency, which contributes to the reduction of carbon emissions (Sovacool et al., 2021). Tourists are the group of individuals whose low carbon behaviors gain researchers' attention: the existing studies aim to investigate what factors influence tourists' travel-related decision-making, such as travel mode (Tattini et al., 2018). The second stream of research focuses on low-carbon consumption behaviors from a consumer study perspective: the types of products individuals or households consume are believed to contribute to carbon emission reduction (Axsen & Kurani, 2012; S. Wang et al., 2016). Given many empirical studies coming from this stream of research, several review papers provide a comprehensive summary of factors affecting low-carbon consumption behaviors (e.g., Ding et al., 2018; T. Wang et al., 2021). It is noted that, rather than assessing the "real" adoption, low-carbon consumption behaviors are measured as consumption intentions in most cases (e.g., Shalender & Sharma, 2021; S. Wang et al., 2016).

However, the above studies only consider one type of low-carbon practices, low-carbon consumption behaviors, or a group of people's low-carbon behaviors, the results of the studies only capture one aspect or a few aspects of low-carbon behaviors. There are only a few studies that consider low-carbon behaviors through the adoption of a variety of low-carbon practices, whilst the majority of studies look into PEs (Asensio & Delmas, 2016). In the context of China, studies on the control of carbon emissions mainly focus on macro-level efforts, with a few exemptions that investigate factors that affect the adoption of a variety of low-carbon behaviors. For example, W. Chen and Li (2019) find that demographic factors, psychological factors, and situational factors (i.e., external factors) influence individuals' low-carbon behaviors, including participating in or encouraging others to take part in environmental protection activities, energy-saving, and using low-carbon transportation (e.g., public transportation and electronic cars). C. Wang et al. (2022) test for the impact of a set of similar factors on low-carbon behaviors and they further find influencing mechanisms are varied across different demographic groups. However, the existing studies ignore an important factor, social influence, in the empirical analysis of low-carbon behaviors. By reviewing studies on energy-saving behaviors, Wolske et al. (2020) find social influence may lead to spatial peer effects on individuals' adoption of energy-saving behaviors, for instance, an individual could be affected by neighbors' energy consumption behaviors.

In light of the above gaps in the literature, this study aims to explore the factors affecting individual residents' low-carbon behaviors, measured by both the adoption or nonadoption of low-carbon practices and the number of adopted practices. Notably, we consider spatial dependence, as a way of social interactions among residents, in their decisions on adopting low-carbon practices.

Methods and Data

Empirical Models

Spatial econometric models were used to address two main questions of the study, including: (1) what factors affect residents' participation in adopting good environmental practices to contribute to achieving carbon neutrality, and (2) what factors affect their choices of the number of low-carbon practices adopted. For the first question, the i^{th} resident is assumed to face the choice of adoption or non-adoption of low-carbon practices. $Y_i(0,1)$ denotes the binary outcome variable and U_{ij} represents the utility associated with the choice $j(j=0,1)$. Hence, the statistical model is driven by the probability of choosing $Y_i(1)$ as $\mathrm{Prob}(U_{i1}-U_{i0}\geqslant 0)=\mathrm{Prob}(Y_i{}^*\geqslant 0)$. $Y_i{}^*$ is a $n\times 1$ latent variable that cannot be observed and is assumed as a function of the observed factors that impact residents' decision-making. These factors are denoted by a $n\times k$ matrix X_i. In addition, we assume that residents' decisions of adopting low-carbon practices are affected by their neighbors' choices (i.e., spatial spillover effects). Therefore, a spatial autoregressive (SAR). Probit model was used to model the spatial dependence of residents' adoption of low-carbon practices:

$$Y_i^* = \lambda W Y_i^* + X_i\beta + \varepsilon_i, \tag{1}$$

where WY_i^* is the spatially lagged dependent variable representing the weighted average utility of the neighboring residents, capturing the spatial dependence of low-carbon behaviors among the residents. λ is the unknown spatial parameter to be estimated. The spatial connections among the observations are modeled by a $n\times n$ spatial weights matrix W defined by the inversed distance $d_{ij}{}^{-1}$ between resident i and j, based on the provided home addresses:

$$w_{ij} = \begin{cases} d_{ij}^{-1}, & 0\leqslant d_{ij}\leqslant d \\ 0 & , d_{ij}>d \end{cases}, \tag{2}$$

where d denotes the threshold distance of 12 km, ensuring every respondent has a "neighbor" in the spatial analysis; and beyond d spatial effects are assumed to be zero. Note that, although all residents living in Kunming City are possibly affected by the same policies or policy instruments, residents are assumed to affect by those living close by (i.e., so-called neighbors) because they may be affected by the ways of promoting environmental protection policies in the same residential compounds; they are also more likely to know the same group of people. We follow (LeSage & Pace, 2009) to estimate the SAR model using the Bayesian Markov Chain Monte Carlo estimation.

We adopted a SAR Poisson model to address the second question concerning the number of low-carbon practices adopted by residents. Similarly, the SAR Poisson model follows the spatial econometric specifications shown in equations (1) and (2), whilst the number of adopted practices y_i is drawn from a Poisson population with the parameter δ_i:

$$\mathrm{Prob}(Y=y_i|X_i) = \frac{\exp(-\delta_i)\delta_i^{y_i}}{y_i!}, y_i = 0, 1, 2, \ldots m. \tag{3}$$

Hence, the SAR Poisson model can be regressed via the following equation:

$$\ln\delta_i = \lambda W y + X_i\gamma. \tag{4}$$

Here, γ is associated with the independent variables to be estimated (Lambert et al., 2010).

Data and Descriptive Statistics

The study is based on a cross-sectional survey conducted between June and August 2021 in Kunming City China. Kunming is the capital city of Yunnan province and the fourth largest city in western China, having a population of 6.73 million (Q. Wu et al., 2015). With the spring-like weather and good ecological environment, Kunming is the horticultural hub and one of the most famous tourist cities in China (D. Wang & Ap, 2013). The commitment to achieve carbon neutrality may help Kunming contribute to the national goal of net-zero 2060 as well as to maintain the good reputation of being an environmental-friendly and livable city (Gössling, 2009). Hence, the survey is designed to understand individuals' pro-environmental practices in their daily lives, including the activities to protect biodiversity and low-carbon practices to help achieve carbon neutrality.

Design of the questionnaires for the survey has undergone two stages. Firstly, the initial questionnaire was tested by a pilot survey where several trained interviewers were sent to three randomly chosen sub-districts, including one district, one county, and one county-level city. Thirty individuals were surveyed and the questionnaires were thoroughly analyzed to get information about the status quo of residents' pro-environmental activities. Following the first stage survey, a structured household questionnaire was finalized. In the second stage, the questionnaire was transformed into a digital survey platform Wen Juan Xing, which is one of the largest online survey platforms in China, and its customers cover 90% of universities and research institutes in China. It was loaded on WeChat so that participants from different regions

Table 1. Definition and Descriptive Statistics of Variables Included in the Study.

Variable	Definition	Mean	*SD*	Min.	Max.	No.
Dependent variable						
Adoption	Dummy, = 1 the respondent thinks he/she contributes, by adopting low-carbon practices, to achieving carbon neutrality in everyday life, = 0 otherwise	0.57	0.50	0	1	694
Extent of adoption	The number of low-carbon practices adopted by the respondent that he/she thinks would contribute to carbon neutrality	3.08	2.26	1	6	393
Independent variable						
Gender	Dummy, = 1 male, = 0 female	0.46	0.5	0	1	694
Ethnicity	Dummy, = 1 Han ethnicity, = 0 otherwise	0.86	0.34	0	1	694
Religion	Dummy, = 1 no religious belief, = 0 otherwise	0.97	0.16	0	1	694
Age	Age of respondent	32.37	14.31	18	90	694
Education	Education level of the respondent (in years)	13	3.91	0	43	694
Income	Annual Income of respondents (10,000 China Yuan)	13.93	14.14	0	130	694
Residence year	Years of living in Kunming	25.93	16.13	0	88	694
Local registration resident	Dummy, = 1 registered local resident of Kunming, = 0 otherwise	0.82	0.39	0	1	694
Occupation	Categorical variable representing the occupation of the respondent					
Government staff	Dummy, = 1 government staff, = 0 otherwise (set as base)	0.118	0.323	0	1	82
Enterprise employee	Dummy, = 1, enterprise employees, = 0 otherwise	0.115	0.32	0	1	80
Farmer	Dummy, = 1 farmer, = 0 otherwise	0.072	0.259	0	1	50
Self-employed	Dummy, = 1 self-employed, = 0 otherwise	0.248	0.432	0	1	172
Retiree	Dummy, = 1 retiree, = 0 otherwise	0.049	0.216	0	1	34
Others	Dummy, = 1 others, = 0 otherwise	0.398	0.490	0	1	276
Park	Dummy, = 1 the resident can access a park from home within 15 min walk distance, = 0 otherwise	0.356	0.425	0	1	694
Reserve	Dummy, = 1 the resident can access a reserve from home within 15 min walk distance, = 0 otherwise	0.135	0.229	0	1	694
Waterways	Dummy, = 1 the resident can access a lake or river from home within 15 min walk distance, = 0 otherwise	0.091	0.256	0	1	694
Perception	Dummy, = 1 the perceived environment of Kunming is good, = 0 otherwise	0.649	0.186	0	1	694
Science communication (SC)						694
Yes	Dummy, = 1 there are science communications (e.g., via noticeboards) in the local community of the resident, = 0 otherwise (set as base)	0.425	0.495	0	1	295
No	Dummy, = 1 no science communications in the local community, = 0 otherwise	0.412	0.421	0	1	285
Don't know	Dummy, = 1 don't know about it, = 0 otherwise	0.163	0.369	0	1	115
Carbon neutrality (CN) knowledge	Dummy, = 1 the respondent has heard of carbon neutrality, = 0 otherwise	0.405	0.491	0	1	694

Note. We exclude zeros (non-contributors) in calculating the descriptive statistic for types of low-carbon practices (i.e., $n = 394$).

can easily participated in online questionnaire survey. The platform is regarded to provide reliable and valid survey respondents (Choi et al., 2020; Zhang et al., 2020). The survey was distributed via sharing the link and QR code through local community offices and residential compounds that can be identified with unique codes, covering all 14 districts, counties, and county-level cities in Kunming. The codes of local community offices and residential compounds in each district are randomly selected and proportional to their share of the total number of households in Kunming (see details of the 14 districts in the Appendix). A total of 1,020 questionnaires were collected, which produces a final sample of 694 completed questionnaires, with 326 questionnaires excluded because of incomplete, erroneous, or being completed in an extremely short time. In this study, we collected information about respondents' low-carbon behaviors, where a simple description of what is CN was given in the survey before asking about their adoptions. Also, we collected the information about the types of practices/activities they conducted, their perceptions of the environment in Kunming City (S. Wang et al., 2018), the demographic and social-economic characteristics (e.g., age, gender, and income) of the respondents (J. Chen et al., 2020; Feng & Reisner, 2011), and the location effects (e.g., close to a park, lake or reserve; Jørgensen et al., 2013). Table 1 reports the definitions and descriptive statistics for all variables used in the empirical analysis.

As shown in Table 1, two dependent variables are considered in the empirical analysis, including the respondents' adoption of low-carbon practices in their daily lives to help achieve carbon neutrality, and the number of low-carbon practices they adopted. It can be observed that more than half of the respondents reported that they adopted low-carbon practices to contribute to achieving carbon neutrality. As for the ways of contributions, the respondents were asked to list the adopted low-carbon practices by typing in text. We use Structured Query Language (SQL) to analyze the text of the descriptions, which produces a word list of low-carbon practices. Keywords selection and categorization for these low-carbon practices were based on existing studies on pro-environment activities and practices (J. Chen et al., 2020; Feng & Reisner, 2011) and low-carbon practices (W. Chen & Li, 2019; C. Wang et al., 2022). For example, "saving energy," "using alternative energy," and "using green energy" are grouped into energy-related practices; "using public transportation" and "reducing the use of private cars" are grouped into transportation-related practices. A total of six groups of low-carbon practices are identified, including transportation-related (e.g., using public transportation, using shared-bicycle/vehicle and walking to work), recycling-related (e.g., using recycling bags/packages, recycling wastes), energy-related (e.g., energy-saving and using renewable energy), afforestation/plantation-related (planting trees, home garden, and volunteer to work for building city gardens/parks), consumption-related (e.g., buying recycled products, consuming less, buying zero-carbon products), and other practices (e.g., sharing information to family and friends about low-carbon practices and promote low-carbon behaviors). It is noted that the recorded low-carbon practices fall into the lists of low-carbon practices/behaviors in the literature (W. Chen & Li, 2019; C. Wang et al., 2022). Given a resident may adopt more than one low-carbon practice, the number of low-carbon practices was then recorded for the second dependent variable—the average number of adopted low-carbon practices is 3.08.

As for the independent variables, the sample shows that the majority of the respondents (82%) are "local" residents (i.e., local registration residents of Kunming) and have lived in Kunming for 25.93 years, on average. The distribution of gender of the sample is relatively even (46% male) and the average age of the respondents is 32.57; their occupations are diverse, including 11.8% government staff, 11.5% enterprise employee, 7.2% farmer, 24.8% self-employed, 4.9% retiree, and 39.8% others. As for the location variables, the proportion of residents having easy accessibility to parks (35.6%), reserves (13.5%), or waterways (9.1%) is found to be relatively low. Regarding the variables of respondents' perceptions of the environment in Kunming, the majority of respondents (65%) confirmed that they like the environment of Kunming. Regarding public science communication, 42.5% of respondents reported that local communities have noticeboards or billboards as a means of delivering information about scientific knowledge, such as climate change and waste management. For residents' knowledge of carbon neutrality, 40.5% of respondents reported that they have heard of carbon neutrality.

Results and Discussion

Factors Affecting Residents' Adoption of Low-Carbon Practices

For comparison purposes, we presented the non-spatial Probit regression model and the SAR Probit model in Table 2. Based on the indicators of model fitness (shown in the bottom rows in Table 2), such as *Loglik*, AIC, and Pseudo R^2 values, the SAR Probit model outperforms the non-spatial Probit model. Also, we employed the Lagrange Multiplier (LM) test and LM robust test to examine the existence of spatial effects in the spatial lag and error term, and the results indicate the existence of the two spatial effects in the non-spatial Probit model. In addition, results of the Wald test show that the spatial Durbin Probit model should be reduced to the SAR Probit model that includes one spatial effect (i.e., the spatially lagged dependent term). Importantly, the spatial coefficient associated with the spatially lagged term, lambda (λ), is found to be positive and significant. This indicates the spatial dependence in residents' decisions of participating in carbon neutrality by adopting low-carbon practices—one's adoption of low-carbon practices is influenced by the neighbors (Läpple & Van Rensburg, 2011; Xu et al., 2006; Yang & Knook, 2021). This finding is inspiring as it indicates the positive spillover effects of low-carbon behaviors: it is not just about one single resident but also the impact from one to a group, a community, and even a city. The existence of the positive spillover effect of low-carbon behaviors may fit into a wider system for a low-carbon city, which aggregates individuals' efforts at a higher level.

The estimation results of the spatial and non-spatial Probit models show a difference in the magnitude and significance level of the estimates of the marginal effects. Here we only interpret the estimation results of the SAR Probit model, which is based on total effects estimates (column 5 Table 2) combining average direct effects and indirect effects (Lacombe & LeSage, 2015; LeSage & Pace, 2009). It is noted that, compared to the demographic (e.g., gender) and social-economic factors (e.g., occupation and income), more variables of perception,

Table 2. Regression Results of Factors Affecting Individual Participation in Carbon Neutrality.

Variable	Probit model	SAR Probit model		
	Average marginal effect	Direct effect	Indirect effect	Total effect
(1)	(2)	(3)	(4)	(5)
Gender	0.073 (0.617)	0.046 (0.033)	0.240 (0.186)	0.286 (0.216)
Ethnicity	0.299 (0.221)	0.085 (0.144)	0.439 (0.351)	0.524 (0.387)
Religion	−1.124 (0.942)	−0.010 (0.094)	−0.056 (0.508)	−0.066 (0.598)
Age	1.745 (1.135)	−0.004 (0.002)***	−0.022 (0.011)**	−0.026 (0.012)**
Education	0.171 (0.001)***	0.016 (0.005)***	0.011 (0.006)***	0.027 (0.003)***
Income	0.265 (0.452)	0.0001 (0.0001)	0.001 (0.001)	0.001 (0.011)
Residence year	0.264 (0.002)***	0.034 (0.013)**	0.007 (0.002)***	0.041 (0.014)***
Local registration residence	0.117 (0.273)	0.014 (0.057)	0.073 (0.300)	0.087 (0.355)
Enterprise employee	−0.673 (0.647)	−0.016 (0.019)	−0.083 (0.52)	−0.099 (0.60)
Farmer	−0.089 (0.4130)	−0.014 (0.290)	−0.012 (0.221)	−0.026 (0.112)
Self-employed	−0.460 (0.629)	−0.081 (0.250)	−0.032 (0.687)	−0.113 (0.169)
Retiree	−0.647 (0.429)	−0.064 (0.192)	−0.083 (0.052)	−0.147 (0.235)
Others	−0.0001 (0.001)	−0.0164 (0.009)	−0.083 (0.052)	−0.099 (0.160)
Park	0.078 (0.362)	0.055 (0.025)***	0.281 (0.143)**	0.336 (0.164)**
Reserve	0.947 (0.445)**	0.037 (0.011)***	0.028 (0.012)**	0.065 (0.012)**
Waterways	0.428 (0.245)**	0.013 (0.011)***	0.009 (0.001)**	0.022 (0.002)***
Perception	−0.027 (0.014)**	−0.207 (0.091)***	−0.072 (0.009)**	−0.279 (0.012)**
SC—No	−0.567 (0.270)**	−0.109 (0.023)***	−0.056 (0.016)***	−0.165 (0.168)***
SC—Don't know	−0.548 (0.307)*	−0.007 (0.123)	−0.006 (0.165)	−0.013 (0.168)
CN knowledge	0.028 (0.015)*	1.206 (0.037)***	0.054 (0.286)***	1.260 (0.292)***
Lambda (λ)	—		0.839 (0.046)***	
LogLik	−1,087.375		−509.258	
Pseudo R^2	0.439		0.459	
AIC	1,048.515		575.15	
LM spatial lag	23.68 ($p < .0001$)			
Robust LM spatial lag	19.21 ($p < .0001$)			
LM spatial error	34.9 ($p < .0001$)			
Robust LM spatial error	21.45 ($p < .0001$)			
Wald test spatial lag			1.482 ($p = .11$)	

*, **, and *** indicate 1%, 5%, and 10% significance levels.

knowledge, and location effects are found to be significant at various significance levels. According to the values of the total effects, the most influential determinants are residents' knowledge of carbon neutrality, science communications to the public, the perceived environmental quality, and the ease of accessing parks. The residents who have heard of carbon neutrality are 126% more likely to adopt low-carbon practices than those who have not, and the 126% total effects can be further broken down to 120.6% direct effects and 5.4% indirect effects. This finding echoes the important role of communication in climate change (Armstrong et al., 2018). The finding is also consistent with the results of studies such as Büchs et al. (2018) and Ding et al. (2018) that highlight the importance of knowledge and awareness of the environmental problem: enhanced knowledge and awareness of climate change or carbon emissions help increase individuals' intentions to adopt low-carbon practices. The residents living in communities that have no public science communications, such as noticeboards and brochures, are 66.5% less likely to participate in carbon-neutral activities (10.9% direct effects and 5.6% indirect effects). The finding is consistent with the extant literature on adoption analysis that information exchange between neighbors, friends, and peers is an important determinant of knowledge diffusion (Autant-Bernard et al., 2013; Zheng et al., 2019), and hence, the information of carbon neutrality can be diffused from neighbors as a positive spillover effect on residents' low-carbon behaviors. Residents' perception of the environment of Kunming is another important determinant of their participation in low-carbon activities: those who find the environment to be not good are 27.9% more likely to take action in protecting the environment toward carbon neutrality. As for the location effects, the accessibility to parks is found to have a positive impact on residents' adoption of low-carbon practices—those having access to a park within a 15-minute walking time are 33.6% more likely to contribute to carbon neutrality. Though smaller, the positive effects are found for the accessibility to reserves and waterways on residents' adoption of low-carbon practices. These findings are aligned with the results of studies on the

Table 3. Regression Results of Factors Affecting the Extent of Individual Participation in Carbon Neutrality.

Variable	Poisson model IRR*	SAR Poisson model IRR
(1)	(2)	(3)
Gender	1.028 (0.258)	1.086 (0.159)
Ethnicity	1.337 (0.110)	0.973 (0.106)
Religion	0.949 (0.265)	0.997 (0.238)
Age	0.974 (0.006)***	0.982 (0.006)***
Education	1.098 (0.001)**	1.008 (0.002)**
Income	1.0001 (0.0001)	1.00002 (0.0001)
Residence year	1.027 (0.005)***	1.022 (0.006)***
Local registration residence	0.997 (0.132)	1.059 (0.138)
Enterprise employee	0.973 (0.020)	0.984 (0.0196)
Farmer	0.983 (0.012)	0.914 (0.019)
Self-employed	0.832 (0.021)	0.786 (0.017)
Retiree	0.767 (0.022)	0.614 (0.018)
Others	0.912 (0.032)	0.458 (0.023)
Park	1.308 (0.026)***	1.856 (0.045)***
Reserve	1.111 (0.046)**	1.813 (0.047)***
Waterways	1.021 (0.004)***	1.032 (0.005)***
Perception	0.629 (0.242)*	0.857 (0.021)***
SC—No	0.747 (0.049)*	0.748 (0.051)***
SC—Don't know	0.471 (0.033)*	0.349 (0.031)***
CN knowledge	1.058 (0.026)*	1.129 (0.077)**
Lambda (λ)	—	0.398 (0.052)***
LogLik	−1,082.78	−895.6
Pseudo R^2	0.467	0.512
AIC	2193.6	986.7
LM spatial lag	23.68 ($p<.0001$)	
Robust LM spatial lag	19.21 ($p<.0001$)	
LM spatial error	34.9 ($p<.0001$)	
Robust LM spatial error	21.45 ($p<.0001$)	
Wald test spatial lag		1.109 ($p=.56$)

Note. *IRR indicates how changes in the independent variables affect the rate at which the number of low-carbon practices occurs (Cameron & Trivedi, 2013). *, **, and *** indicate 1%, 5%, and 10% significance levels.

relationship between residents' willingness to pay (WTP) to improve environmental quality and their hedonic demand for beautiful scenery—their WTP decrease with the increase of the distance from their houses to the park, reserve, or river (Bateman et al., 2006; Jørgensen et al., 2013). In addition, the significant location effects on adoption are consistent with the results of many PEs studies: access to support and resources positively affect individuals' low-carbon behaviors (e.g., Armstrong et al., 2018; Moloney et al., 2010; Schäfer et al., 2018).

Among all the demographic and social-economic factors, years of residence, age, and education are important determinants of residents' adoption of low-carbon practices. Older residents are less likely to adopt low-carbon practices; residents having higher education or longer years of residence in Kunming have a higher propensity to adopt low-carbon practices. The findings of age and education effects are consistent with the previous studies that residents having higher education are more likely to participate in pro-environmental activities (Armstrong et al., 2018; Chawla & Cushing, 2007); younger adults seem to be more worried about climate change than older adults (Clayton, 2020), and hence are more likely to take actions to deal with it. These findings are consistent with the existing studies that address the influencing mechanism through demographic factors, such as education (W. Chen & Li, 2019; C. Wang et al., 2022). Residents who have lived in Kunming for a longer time promote to participate in low-carbon activities, regardless of their registered residence status (hukou) in Kunming or other regions. This finding indicates that the "sense of belonging" is more likely to come from the time they live and spend in one place (i.e., social identity) rather than the registered residence status on the official records (Brieger, 2019). Other factors, including gender, ethnicity, religion, and occupation, are found to have no impact on the likelihood of residents' participation in adopting low-carbon practices.

Factors Affecting the Extent of Low-Carbon Practice Adoption

Table 3 presents the results of the non-spatial Poisson model and the SAR Poisson model. For interpretation purposes, the coefficient estimates of the two models are exponentiated to derive the incidence rate ratio (IRRs) as they are directly interpretable and provide meaningful insights into how different factors influence the extent of low-carbon practice adoption. According to the indicators of model fitness and test results (shown at the bottom of Table 3), the SAR Poisson model performs better than the non-spatial Poisson model, and the spatially lagged dependent term should be considered in modeling the impacts of factors on the extent of low-carbon practice adoption, that is, the number of low-carbon practices adopted by residents. In addition, the spatial parameter λ associated with the spatially lagged dependent variable is found to be positive and significant, indicating the spatial dependence in the extent of residents' adoption of low-carbon practices. Hence, our interpretation is based on the IRRs estimated through the SAR Poisson model.

Conclusion

This study provides novel insights into understanding residents' low-carbon behaviors in China. Besides analyzing residents' adoption of low-carbon practices, we examine the extent of adoption by analyzing the open-ended question of types of low-carbon practices given by residents—the text analysis and categorization of the practices provide some insights into understanding residents' knowledge of low-carbon practices. Using spatial econometric models, the empirical analysis contributes to the literature by providing evidence of the key factors, including knowledge and science communication of carbon neutrality and location effects (e.g., accessibility to parks and lakes) that affect residents' adoption and the extent of adoption of low-carbon practices. Spatial dependence is found amongst residents' adoption and extent of adoption of low-carbon practices, indicating the positive spillover effects of low-carbon behaviors from the neighboring residents. In addition, age, education, and years of residence are the characteristics of residents that affect their low-carbon behaviors.

The results have important policy implications for the design of policy to motivate residents' adoption of low-carbon practices. First, residents' interactions need to be considered in the adoption of low-carbon practices because of the existence of spatial effects in low-carbon behaviors. Funding or policy support for organizing seminars, workshops, or conferences may help the spillover of low-carbon behaviors among residents—through the interactions between the participants and their social networks, such as their neighbors and neighbors' neighbors (Yang & Knook, 2021). Second, to achieve a higher adoption of low-carbon practices, policymakers should consider efficient ways of diffusing the knowledge of climate change and communicating carbon neutrality to the public. As suggested by our results, the local community can be a trustworthy channel/source for residents to get scientific knowledge. Third, the government may consider supporting the improvement of green space, such as parks and gardens that are found to be the hedonic driver for residents to adopt low-carbon behaviors.

Due to the data limitation (only based on one city in China), further research on low-carbon behaviors may consider expanding the sample size to include more cities and regions and testing for the spatial effects as well as the impacts of the key factors identified in this study. In addition, the study may be limited by the fact that only a quantitative research method was adopted, whilst qualitative research methods, such as semi-structured interviews and focus group discussion, could also be applied to gather a more comprehensive understanding of how these included factors influence residents' low-carbon behaviors. Last, the models developed in the current paper could be used and further tested in future studies to conduct comparisons, particularly where more data on different cities or regions are collected.

Authors' Contributions

Wei Yang and Yao Lu co-lead the paper as they have equal contributions to the study. Here are the specific contributions of each author: Wei Yang: Methodology, Conceptualization, Data analysis, Investigation, Writing, Reviewing, and Editing. Yao Lu: Conceptualization, Data analysis, Investigation, Editing, and Funding acquisition. Le Wang: Data analysis and Writing. Yang Xu: Investigation and Reviewing.

Declaration of Conflicting Interests

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Ethical Approval

Survey of the study is approved by the human ethics committee of Yunnan agricultural university.

Consent to Participate

The consent form for survey participants is approved by the human ethics committee of Yunnan agricultural university. Survey participants were first provided the consent form regarding their willingness to take part in the study before taking the survey, and they were informed that they can withdraw the survey at any time.

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Data Availability Statement

The datasets generated during and/or analyzed during the current study are not publicly available due to the anonymous and confidentiality agreement with the survey participants.

Supplemental Material

Supplemental material for this article is available online.

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