

Article

Spatial Spillover Effects of Urban Gray–Green Space Form on COVID-19 Pandemic in China

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Abstract: Although the immediate impact of the COVID-19 pandemic has been alleviated, its long-term effects continue to shape global health and public safety. Policymakers should prepare for potential future health crises and direct urban planning toward more sustainable outcomes. While numerous studies have examined factors influencing the risk of COVID-19, few have investigated the spatial spillover effects of urban form and green space. In this study, we quantified urban form using landscape pattern indices, represented population mobility with the Baidu Migration Scale Index, and assessed the role of key influencing factors on the epidemic through STIRPAT and spatial Durbin models. Our findings reveal that population migration from Wuhan had a significant local impact on the spread of COVID-19. These factors not only intensified local transmission, but also triggered positive spatial spillover effects, spreading the virus to neighboring regions. We also found that green space connectivity (pc_5) plays a crucial role in reducing the spread of the virus, both locally and in surrounding areas. High green space connectivity helps mitigate disease transmission during an epidemic. In contrast, the spatial configuration and unipolarity of urban areas (pc_1) contributed to the increased spread of the virus to neighboring cities. Ultimately, balancing building density with green space distribution is essential for enhancing urban resilience. This research provides new insights into sustainable urban planning and helps us understand the impact of the spillover effects of gray–green space forms on public health and safety.

Keywords: COVID-19; population mobility; spillover effects; urban form; green space connectivity



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1. Introduction

COVID-19 pandemics pose unprecedented challenges to human health and public safety. Urban public spaces, such as squares, streets, and parks, are not only central to social interactions, but they are particularly important for the prevention and control of respiratory infections in dense urban environments [1]. The accurate risk assessment of urban spaces and in-depth analysis of their mechanisms of action in the dynamics of disease

transmission are key prerequisites for the development of targeted prevention and control strategies [2]. This view is also shared by numerous scholars, who generally agree that the COVID-19 crisis provides an opportunity to push urban planning in a more sustainable direction [3,4].

Traditional risk assessment methods rely on epidemiological surveys and case statistics [5], which are quick to respond but lag behind the actual situation and make it difficult to undo the damage caused. In contrast, the proactive optimization of urban spatial structure, especially the rational allocation of gray and green spaces, can effectively reduce the negative impacts of public health events and be consistent with long-term sustainable development goals [6]. Numerous studies have shown that green spaces not only help to improve the mental health of residents, but also reduce the risk of virus transmission by reducing crowd congregation and improving air circulation [7]. Conversely, high-density built environments may exacerbate the spread of epidemics and affect urban resilience [8]. Given the context of climate change, rapid urbanization, and the continued degradation of global ecosystems, the frequency of public health emergencies is expected to continue to rise in the future, posing serious challenges to urban resilience and public health [9]. In this context, the in-depth exploration of the impact of urban gray-green spatial patterns on epidemic transmission mechanisms has become a research direction that requires urgent attention. Quantitatively analyzing the influence of different urban gray-green spatial patterns on the risk of epidemic transmission not only helps to reveal the role of spatial patterns in the spread of health risks, but also provides theoretical support for the development of more forward-looking urban planning strategies so as to more effectively respond to possible future public health crises and realize the sustainable and healthy development of urban space.

Sustainable and healthy cities are currently a top priority, encompassing economic, ecological, and environmental dimensions. As the pandemic stabilizes, policymakers must plan ahead for potential future health crises. This requires forward-looking decisions and urban designs that optimize resources and improve ecological environments. While numerous studies have examined the factors influencing COVID-19 risk, few have considered the spatial spillover effects of urban form and green space. Spatial patterns can guide population movements and, thus, offer significant insights for sustainable urban development. As research on COVID-19 evolves, it has moved beyond single-factor analyses toward more comprehensive approaches that consider socio-economics, natural environments, and ecosystem changes; factors that collectively shape the emergence, spread, prevention, and control of epidemics. These influences can be broadly grouped into five categories: (1) Social factors: population mobility, density, household composition, ethnicity, and smoking habits significantly affect how the virus spreads [10–12]. (2) Economic factors: urbanization, international trade, occupational patterns, income levels, proximity to outbreak sources, health resource distribution, and transportation modes play key roles in viral transmission [10,11,13,14]. (3) Policy measures: lockdowns, time-restricted social interactions, and border closures are integral to controlling outbreaks [15–17]. (4) Natural environment: encompassing factors like temperature, humidity, sunlight, radiation, wind speed, pressure, rainfall, elevation, and air pollution, which also influence transmission risk [18–20]. (5) Ecological factors: changes in land use, loss of biodiversity, and variations in green space coverage alter the distribution of hosts and vectors, thereby affecting virus spread [21–23]. While the relationship between spatial variables and infectious diseases has long been recognized, most COVID-19 studies have emphasized socio-demographic elements over spatial factors like urban geometry. To gain a more complete understanding of COVID-19 transmission and improve future response strategies, it is essential to integrate these spatial dimensions into ongoing research.

The relationship between coronavirus transmission and urban spatial patterns is complex and not yet fully understood, especially for how the arrangement and combination of gray and green spaces in cities affect epidemic dynamics, which need to be explored in depth. Hu et al. (2023) argued that compact urban development patterns optimize spatial use but may exacerbate the risk of the transmission of infectious diseases due to the increase in the frequency of interpersonal contact [24]. Urban core areas are often dominated by high-density “gray” infrastructure (e.g., buildings, roads, etc.), and the gray spatial pattern not only limits the physical distance of social interactions, but also affects viral transmission by increasing the level of crowding and the frequency of public transportation use [25,26]. Liu et al. (2021) assessed the impact of the built environment on the COVID-19 risk of infectious diseases in the following study on the impact of the built environment on COVID-19 morbidity. They found that dense built environments lead to the congregation of people, accelerating the spread of droplet-transmitted diseases such as COVID-19, whereas increased open space is beneficial in reducing morbidity [27]. At the same time, the challenges posed by COVID-19 highlight the importance of strengthening and expanding green infrastructure [28]. Studies have shown that green spaces such as parks, courtyards, and gardens not only improve the mental health of residents, but also indirectly reduce the risk of airborne virus transmission by mitigating air pollution and improving public health outcomes [29–31]. For example, Liu and Wang’s (2021) study pointed out that pocket parks can fill vacant urban spaces and provide health support and social functions for high-density neighborhoods [32] and You et al. (2020) emphasized that the ecological function of urban green space has a positive effect on slowing down the spread of COVID-19 [33]. However, most of the existing studies have focused on exploring the impact of gray space or green space on epidemic transmission alone, and few have explored the impact of the integrated layout of gray and green spaces and their spatial spillover effects on epidemic transmission.

Cities should be viewed not as a mere patchwork of gray and green spaces, but as complex systems with interconnected elements that require thoughtful and integrated design [34]. This broader understanding influences human well-being and affects the survival and development of other species. Within this framework, gray and green spaces exist in a nested interdependent relationship that shapes the city’s overall spatial structure. Gray spaces primarily support human activities, while green spaces offer essential ecological services. Together, these elements create distinct urban landscapes that, under certain conditions, can combine into higher-level systems, enhancing both urban and ecological functions [35]. Many current studies attempt to quantify spatial characteristics simply by measuring certain land areas [36,37]. However, recent research on COVID-19 often neglects the importance of spatial structure, arrangement, and composition, paying little attention to urban landscape patterns that have been shown to influence other infectious disease outbreaks. To better understand the transmission mechanisms of COVID-19, it is essential to emphasize these urban designs and geometric factors and integrate them into future research.

In summary, this study focuses on the period from 23 January to 1 March 2020, capturing the time before and after the outbreak of COVID-19. It quantifies urban gray–green space patterns using landscape pattern indices and applies principal component analysis (PCA) to reduce these indices to seven key components. Using these components as core variables, alongside socio-economic and ecological factors as controls, this study employs the spatial Dubin model (SDM) to examine the spatial spillover effects of gray–green space configurations both locally and in adjacent areas. By using the spread of COVID-19 as a point of reference, this research investigates how urban gray–green space patterns influence the epidemic’s transmission risk. It provides quantitative evidence on

the relationship between gray–green space configurations and the likelihood of disease spread. In doing so, it offers a new perspective on ecological city development, enriches the theoretical understanding of gray–green spaces and epidemic prevention, and provides insights that can inform urban planning and guide sustainable ecosystem development.

2. Materials and Methods

The aim of this study is to investigate the spatial spillover effects of urban gray–green spatial patterns on the spread of COVID-19. To this end, this study adopted an integrated spatial analysis approach. First, the gray–green spatial patterns of the city were quantified by landscape pattern indexes, and several related indicators were downscaled using principal component analysis (PCA), from which seven main components were extracted to comprehensively characterize the structural features of the urban gray–green spaces. Subsequently, the relationship between these gray–green spatial features and the spread of the epidemic was analyzed using the spatial Durbin model (SDM), especially their direct impact on the local epidemic spread and the spatial spillover effect to neighboring areas. To further explore the drivers of epidemic spread, this study also combined multidimensional variables such as ecological, socio-economic, and population mobility to comprehensively assess the role of these factors in epidemic spread. In addition, through the global Moran index and local spatial autocorrelation analyses, we have deeply explored the spatial distribution characteristics of the epidemic spread. The operational workflow is illustrated in Figure 1.

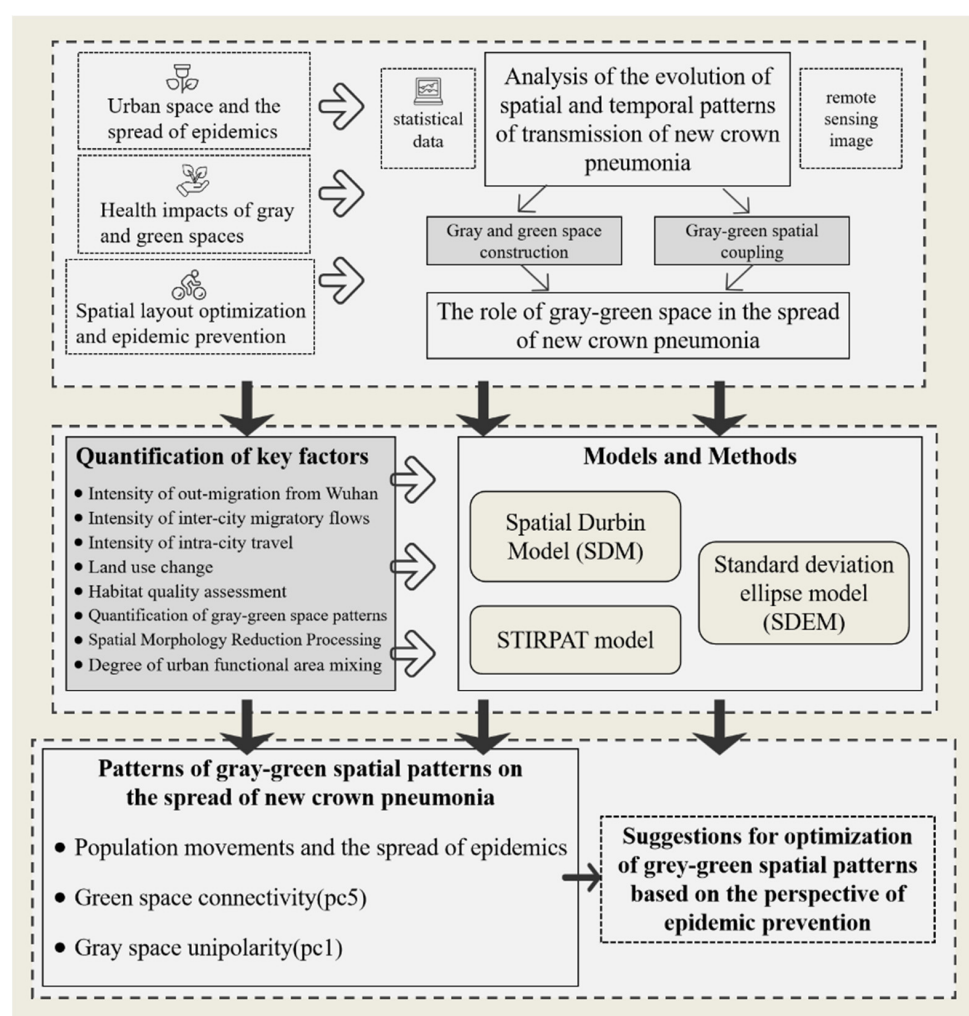


Figure 1. Research flow chart.

2.1. Standard Deviation Ellipse Model

The Elliptical Standard Deviation (ESD) Model is a statistical technique used to quantify the dispersion of data points within a spatial distribution. It is particularly useful for analyzing datasets with asymmetric or biased distributions. The model represents the distribution characteristics of the data by drawing an ellipse, where the lengths of the ellipse's axes correspond to the standard deviations of the data in different directions, and the orientation of the ellipse reflects the covariance between the variables [38]. This model allows for a clear depiction of how data points are spread out in different directions and highlights the relationship between these directional dispersions. It is especially valuable in spatial data analysis where the data shows varying levels of dispersion and correlation across dimensions [39]. The calculation for the ellipse's center is as follows:

$$SDE_x = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{X})^2}{n}} \quad (1)$$

$$SDE_y = \sqrt{\frac{\sum_{i=1}^n (y_i - \bar{Y})^2}{n}} \quad (2)$$

where x_i and y_i represent the spatial location coordinates of each city's COVID-19 cases and $\bar{X}$ and $\bar{Y}$ denote the arithmetic mean center of COVID-19 cases.

2.2. STIRPAT Model and Multiple Variable Regression

IPAT is a well-established formula used to analyze the environmental impacts of human activities. Developed during the Ehrlich–Holdren/Commone debates in the early 1970s, it has since served as a common framework for examining how population size (P), wealth (A), and technology (T) influence environmental outcomes [40]. The *IPAT* formula is expressed as follows:

$$I = P \times A \times T \quad (3)$$

where I denotes environmental impact, P denotes population size, A denotes wealth, and T denotes technology level.

Population size, wealth, and technology level were chosen as core variables for the *IPAT* model, initially to illustrate that social factors such as demographics and economics can drive environmental pressures in conjunction with technology levels, and to include key anthropogenic drivers in the model in a succinct manner [41]. In this study, population size, wealth, and technology level are strongly associated with the phenomenon of viral transmission in cities: population size is directly related to the physical conditions for viral transmission, with densely populated areas tending to have a higher frequency of interpersonal contact, which may facilitate the spread of viruses; economically developed areas are more likely to have well-developed outbreak resilience facilities, such as medical equipment; and the level of science and technology closely influences outbreak monitoring, intervention, and response, e.g., the efficiency of big data in tracking close contacts has a direct impact on interrupting the spread of an outbreak.

Despite its simplicity and intuitive nature, the *IPAT* model fails to capture and explain the extent to which the individual elements of the model influence the results, as it assumes that the three factors mentioned above act in a linear and equiproportional manner in terms of their impact on the environment.

Recognizing the limitations of *IPAT*'s fixed factors, scholars developed the *STIRPAT* model to allow for a more flexible and stochastic analysis [42]. The original *STIRPAT* model is given by the following.

$$I = aP^b A^c T^d e \quad (4)$$

In this model, a is a constant, b , c , and d are elasticity coefficients indicating how a 1% change in P , A , or T affects I by $b\%$, $c\%$, or $d\%$, respectively, and e is a random error term. Taking the natural logarithm of both sides (when $a = b = c = d = e = 1$) results in the following.

$$\ln I = \ln a + b(\ln P) + c(\ln A) + d(\ln T) + \ln e \quad (5)$$

The elasticity coefficient is an important improvement of the *STIRPAT* model relative to the *IPAT* model, and is also one of the core parameters of the *STIRPAT* model. In view of the shortcomings of the *IPAT* model, which can only portray the equiproportional linear relationship, the *STIRPAT* model, by introducing the elasticity coefficient, is able to reveal the nonlinear intensity and direction of the effect of different independent variables on the dependent variable, and, thus, is able to more accurately characterize and portray the complex mechanism between the independent variable and the dependent variable [43].

Although *STIRPAT* is more flexible than *IPAT*, it still focuses primarily on population, economic growth, and technology, overlooking other important factors such as urbanization, industrial structure, and energy consumption patterns. To address these gaps, we extended the model to include a broader set of socio-economic, ecological, and spatial indicators.

The three dimensions of socio-economics, ecological environment, and urban form were chosen to study the risk of epidemic transmission, which correspond to the transmission drive, natural constraints, and spatial carriers, respectively, and can further improve the *STIRPAT* model. The socio-economic dimension can explain the driving force of human activities on the spread of COVID-19, which includes elements such as population movement; in the ecological environment dimension, factors such as climatic conditions and air quality directly affect the spread efficiency of COVID-19; and the urban form dimension influences and regulates the exposure of the population and the spread of the virus through the pattern of gray and green spatial landscapes.

Based on the consideration of the three major dimensions of socio-economics, ecological environment, and urban morphology, and combining the results of previous studies, the following typical control variables were included in this study: (1) Wuhan migration outflow scale index: Studies conducted from a demographic perspective have generally concluded that population mobility accelerates the spread of epidemics, and the outflow of people from the place where the epidemic occurs is the most important factor for the increase in disease cases in other areas. The outflow of people from the area where the epidemic occurred is the most important factor for the increase in cases in other areas. (2) Intra-city travel intensity: In addition to the inter-city movement of population, the population within the city is also prone to close contact with other people through transportation and daily activities, which leads to the spread of the virus within the city [44]. (3) Patch size, patch shape, and patch connectivity: By influencing the natural environment and human behavior, gray-green space can control the source of infection and block the transmission pathway, thus preventing the spread of the epidemic [45].

In addition, for each indicator, the detailed selection basis is shown in Table 1.

Our goal was to examine the factors influencing the spread of COVID-19, measured by confirmed cases (cm), and to assess the role of spatial patterns. The expanded model can be written as follows.

$$\ln cm = \ln a + \beta_1(\ln wh\_q) + \beta_2(\ln qxqd) + \beta_3(\ln cncx) + \beta_4(\ln popd) + \beta_5 \ln(dfzc) + \beta_6 \ln(yycx) + \beta_7 \ln(roads) + \beta_8 \ln(entroy) + \beta_9 \ln(edu) + \beta_{10} \ln(tem) + \beta_{11} \ln(pro) + \beta_{12}(\ln wind) + \beta_{13} \ln(pm_{2.5}) + \beta_{14} \ln(pc1 \sim pc6) \quad (6)$$

Among them, for socio-economic aspects, we included the amount of people moving out of Wuhan (*wh_q*), the intensity of inter-city migration (*qxqd*), the intensity of intra-city travel (*cncx*), the population density (*popd*), the public budget expenditure (*dfzc*), the number of hospital beds (*yycw*), the density of roads (*roads*), the degree of mixing of urban functions (*entroy*), and the level of education (*edu*); for ecological and environmental aspects, we included average daily temperature (*tem*), precipitation (*pro*), wind speed size (*wind*), and air pollution level (PM_{2.5}); for gray-green spatial patterns aspects, we included principal components generated by the downscaling of the landscape pattern index (Table 1). The core indicators are Wuhan out-migration volume (*wh_q*), intra-city travel intensity (*cncx*), PM_{2.5}, and gray-green spatial form, and the rest of the indicators are included in the control variables in order to prevent the omission of variables so that the model simulation becomes smooth. Except for the spatial form indicators obtained from principal component dimensionality reduction, which are not logarithmic (standardization was performed during dimensionality reduction analysis), the other indicators need to be logarithmic in order to eliminate the effect of the magnitude level, which can avoid pseudo-regression and eliminate heteroskedasticity in the equations.

Table 1. Basis for the selection of indicators.

Dimension	Variable	Selection Basis
Socio-economic	Wuhan migration outflow scale index	Studies from a demographic perspective have focused on the impact of population mobility on the spread of the epidemic, and it is generally recognized that population mobility accelerates the spread of the epidemic and that the outflow of people from Wuhan is the most important factor influencing the number of cases in each location. Accordingly, the Wuhan city lockdown to limit the population was key to the rapid and effective control of the epidemic [44,46].
	Inter-city migration intensity	
	Intra-city travel intensity	
	Population density	Several studies have shown that COVID-19 spreads more rapidly in areas with high population densities than in areas with low population densities [47,48].
	Public budget expenditure	Local government expenditures on various activities in the region can reflect the efforts of local governments in responding to the spread of COVID-19 [49].
	Number of hospital beds	It reflects the level of local medical conditions. Timely admission for treatment and the isolation of cases will reduce the probability of spreading the epidemic [50].
	Road density	It reflects traffic road transportation. Average distance traveled and commuting distance may be associated with higher incidence of COVID-19 transmission, and reduced travel during an outbreak is important in delaying outbreaks [51].
	Education level	The higher the level of education of the people, the greater the awareness of self-protection and the conscientious implementation of the quarantine policy, which is conducive to the implementation of policies formulated by the government and the control of the spread of the epidemic [52].

Table 1. *Cont.*

Dimension	Variable	Selection Basis
Ecological environment	Daily average temperature	Studies have shown that ecological environment and climatic conditions, as the main ways and influencing factors of virus transmission and population infection, play an important role in the occurrence, development, spread, prevention, and control of the epidemic. Temperature, wind speed, rainfall, and air particulate matter concentration play an important role in the spread of the virus [53]. Low temperature, low humidity, and a high concentration of air particulate matter exposure are more conducive to the spread of coronavirus in the environment [54]. Air pollution such as inhalable fine particulate matter (PM _{2.5}) is an important risk factor for the COVID-19 epidemic [55,56].
	Precipitation	
	Wind speed	
	Air pollution level	
Urban Form	Patch size	In most cases, green area and green rate are used to quantify landscape features, while their spatial configuration is ignored. However, more complex and fragmented landscapes are associated with more ecological processes, which increases the possibility of contact with various infectious diseases [57]. As urbanization has accelerated the exchange of people, the compression of space has provided a hotbed for the spread of the epidemic and enhanced the ability of the virus to spread. The urban gray building and ecological green space form a way of integration and blocking [58]. The gray–green space can control the source of infection, block the route of transmission, and protect the susceptible population directly or indirectly by affecting the atmospheric environment and controlling human behavior, and prevent the spread of the epidemic by inhibiting the epidemic conditions of infectious diseases [45]. At the same time, gray–green space can affect the climate through ecological effects, and can greatly affect the spread of urban COVID-19 by providing ecosystem services and as an urban disaster shelter [59]. The composition and degree of mixing within urban functional areas significantly influence the spread of the COVID-19 virus.
	Patch polycentricity	
	Patch shape	
	Patch fragmentation	
	Patch connectivity	
	Patch compactness	
	Patch sprawl	
	Urban functional mixing degree	

2.3. Spatial Econometric Model

Spatial measurement models are essential tools for analyzing how spatial relationships influence outcomes in urban studies. These models are primarily divided into three types: the spatial lag model, the spatial error model, and the spatial Durbin model [60]. Each model addresses different sources of spatial effects within spatial autoregressive processes. Traditional regression models often overlook unobservable factors such as geographical proximity, infrastructure accessibility, trade policies, and cultural exchanges. These omitted variables can lead to biased results because they introduce spatial autocorrelation, where observations near each other are more similar than those further apart [61]. To address this issue, spatial measurement models incorporate spatial correlation directly into the regression framework. In spatial systems where each region has a single observation, the error terms can be modeled as spatially structured random effects. This approach assumes that neighboring regions exhibit similar effect levels due to their proximity. Spatial systems frequently involve externalities that depend on independent variables, further influencing the dependent variables across regions. The spatial lag model specifically addresses these externality dynamics by including explanatory variables from neighboring regions. This inclusion allows the model to capture the impact of independent variables across different geographic units. The spatial Durbin model extends the spatial lag model by incorporating

both spatially lagged dependent and independent variables. This dual inclusion provides a more comprehensive understanding of how both the outcomes and the predictors in neighboring regions affect the focal region [60]. Choosing the appropriate spatial model—spatial lag, spatial error, or spatial Durbin—depends on the underlying drivers of spatial effects, such as omitted variables, spatial heterogeneity, or externalities. This selection introduces uncertainties related to model type, parameter estimation, and the specification of explanatory variables. Consequently, studies investigating spatial effects must carefully consider these factors to ensure robust and reliable results.

Spatial dependence effects can be the result of interactions between endogenous and exogenous interactions between regions and error terms with autocorrelation.

$$Y_{i,t} = \alpha + \rho \sum_{j=1}^n W_{i,j} Y_{i,t} + \beta X_{i,t} + \theta \sum_{j=1}^n W_{i,j} X_{i,t} + \sigma_i + u_t + \varepsilon_{i,t} \quad (7)$$

$Y_{i,t}$ is the dependent variable in year t for the i th city, α is a constant term, $\rho \sum_{j=1}^n W_{i,j} Y_{i,t}$ denotes the spatial interaction between the dependent variables, ρ is the spatial autoregressive coefficient, $W_{i,j}$ is the spatial weight matrix created, $X_{i,t}$ is the independent variable, β is the regression coefficient of the independent variable X reflecting the effect of the independent variable on the dependent variable, u_t is the period-specific effect, σ_i is the spatial-specific effect, $\varepsilon_{i,t}$ is an independent and identically distributed random error component with mean 0 and variance σ^2 , and $v_{i,t}$ is the spatial error term in the presence of the variable.

2.4. Variables and Data Source

2.4.1. COVID-19 Infection Rate

This study focuses on prefecture-level cities and above in China, encompassing a total of 252 city units across 22 provinces, 5 autonomous regions, 4 municipalities directly under the central government, and 15 sub-provincial and prefectural-level cities (excluding Hong Kong, Macao, and Taiwan). The daily confirmed COVID-19 case data were sourced from the National Health Commission's publicly available online dataset, covering the period from 23 January to 1 March 2020 (http://www.nhc.gov.cn/mohwsbwstjxxzx/new_index.shtml (accessed on 21 May 2023)). While Wuhan and its neighboring cities implemented lockdown measures in late January to restrict movement, the incubation period of COVID-19 (approximately 10 days) led to subsequent outbreaks in nearby provinces, such as Henan, Anhui, Jiangxi, and Hunan. These regions experienced increasingly severe outbreaks throughout February, with infection rates gradually declining from Wuhan and Hubei Province toward peripheral areas. This study analyzes two distinct periods: the outbreak phase (up to 12 February) and the control phase (up to 1 March). This timeframe, spanning from late January to early March, was selected because it represents the peak of the national epidemic, prior to the influence of overseas imports and sporadic outbreaks that began after April.

2.4.2. Baidu Migration Scale Index

Baidu Migration Big Data does not provide specific population figures for Wuhan's out-migrating population, but instead reports the percentage of people leaving the city to another city on a given day relative to the total number of people leaving Wuhan that day (<https://qianxi.baidu.com/#/> (accessed on 23 May 2023)). Additionally, the City Migration Scale Index reflects the overall size of a city's in-migrating or out-migrating population, allowing for horizontal comparisons between cities. To ensure the comparability of migration data across cities and time periods, this study calculates a migration scale index by multiplying the daily percentage of people migrating from one city to another by the index of the total number of people leaving that city at the same time [62]. This provides an

estimate of the migration scale, which can be used to assess the volume of out-migration from one city to others. A similar approach is applied to calculate the migration scale index for the flow of people from other cities to the destination city.

$$PM_k = \sum_i^n PR_{tk} \times PS_t \quad (8)$$

PM_k represents the population outflow scale index from a certain city to city k , PR_{tk} represents the percentage of the population migrating from that city to city k at time t , and PS_t represents the migration scale index of that city at time t .

Inter-city population migration data are sourced from Baidu Migration, a travel map service provided by Baidu, China's largest search engine (<https://qianxi.baidu.com/#/> (accessed on 23 May 2023)). The data are based on real-time location records from smartphones using Baidu's mapping app v15.0.0, offering precise insights into population movements between cities. The Baidu Migration dataset includes daily migration data for 120,142 city pairs across 364 Chinese cities, covering the period from 12 January to 12 March in 2019 and from 1 January to 29 February in 2020. This period corresponds to 24 days before and 36 days after the Spring Festival for the respective years, according to the lunar calendar. The dataset contains a total of 2,977,899 city-pair observations for each year (<https://qianxi.baidu.com/#/> (accessed on 23 May 2023)). Additionally, Baidu provides daily within-city mobility data, which consist of 21,840 city-day-level observations annually.

2.4.3. Quantifying Spatial Patterns

Urban form refers to the physical layout and spatial distribution of elements within a city. With advancements in big data technology, geographic information systems (GIS), and remote sensing, urban spatial form can now be quantified using landscape indicators. Numerous studies have employed ecological landscape indices to describe urban form, as these indicators capture information from remotely sensed images and provide insights into landscape conditions and land use patterns [63–66]. Urban landscapes are composed of two primary components: gray architectural space (gray space) and green ecological space (green space). Green space is a vital part of ecological infrastructure, while gray space represents the built environment. A harmonious integration of both is essential for creating cities where humans and nature coexist. Landscape indices condense landscape pattern information, reflecting the structural composition and spatial configuration, and quantitatively describing the evolution of landscape patterns and their ecological impacts. A variety of landscape indices are applied together to comprehensively represent landscape pattern characteristics and connect them to specific ecological processes. These indices are calculated using Fragstats 4.2 and include the following.

Patch size: ① Total area (TA) and ② percent of landscape (PLAND); urban scale refers to the total area of all patches, which is an important indicator for describing the overall scale and expansion of a particular landscape, and is also the basis for calculating other spatial indicators. (2) Patch polycentricity: The largest patch index (LPI), reflecting the direction and strength of human activities, can be used to measure the degree of urban monocentricity. (3) Patch shape: ① Area-weighted mean shape index (AWMSI), ② landscape shape index (LSI), and ③ area–fractal dimension (PAFRAC), which is one of the most important indicators for measuring the complexity of the spatial pattern of the landscape and has an impact on many ecological processes. When these three indices values increase, it means that the shape of the patches becomes complex and more irregular. (4) Patch fragmentation: ① Number of patches (NP), ② landscape division index (DIVISION), and ③ Euclidean nearest neighbor distance (ENN_MN) are often used to

describe the heterogeneity of the whole landscape. The size of their values has a good positive correlation with the fragmentation degree of the landscape, and the general rule is that a large value is associated with a high degree of fragmentation. (5) Patch connectivity: ① Patch cohesion index (COHESION) and ② Connectance Index (CONNECT) reflect the functional connectivity between landscape components. When the structure of landscape components favors the connectivity between landscape components, the proportion of functional connectors connected is higher, which is conducive to the material, energy, information, and other ecological flows running between landscape patterns. (6) Patch compactness: (1) Clumpiness (CLUMPY) and (2) percentage of like adjacencies (PLADJ) can be used to indicate the degree of aggregation of urban patches. This index is minimized if the urban patches are maximally dispersed, and maximized if the urban patches are maximally aggregated. (7) Patch spreading: ① Aggregation index (AI) and ② Contagion index (CONTAG), contain spatial information and are two of the most important indices describing the landscape pattern; in general, a high spreading value suggests that a certain dominant patch type in the landscape forms good connectivity, and conversely suggests that the landscape is a dense pattern with a variety of elements.

We selected and calculated the above 15 indexes from 7 different types of landscape indices for both green space and gray space, with a total of 30 indexes, to analyze the structural characteristics of urban gray–green spatial patterns. This way of assessing spatial patterns by selecting multiple landscape indices can better cope with the complexity of the landscape system, and the complementarity between different indices can avoid one-sided conclusions, thus reducing the analysis bias and realizing a comprehensive and multidimensional assessment of the structural characteristics of urban gray–green spatial patterns. Since multiple indicators may represent the same attribute, there is likely a high correlation among the variables. In particular, the gray–green spatial combination indicators tend to be highly correlated, which can complicate the attribution analysis in a multiple regression model and introduce bias. To address this, we applied principal component analysis (PCA) to reduce the dimensionality of the gray–green spatial form indicators. PCA is a widely used technique for dimensionality reduction, aiming to transform multiple correlated indicators into a smaller set of uncorrelated composite indicators [67]. To obtain the results of the principal component analysis, the number of principal components obtained has to be equal to the number of input variables, and we need to complete further screening according to certain criteria to achieve the purpose of dimensionality reduction. Generally speaking, the eigenvalue of the selected principal components needs to be greater than 1 and the cumulative contribution rate needs to be greater than a certain threshold to retain most of the information of the original data. Based on the cumulative contribution of principal components (value > 80%), eigenvalues > 1, and the scree plot, seven principal components were selected to comprehensively characterize the gray–green spatial pattern, as seen in Table 2. The $\cos^2$ values indicate the importance of each variable in the principal components, with higher values suggesting a stronger contribution. Variables with high $\cos^2$ values are plotted closer to the edge of the correlation circle, while those with low values appear near the center. Figure 2 show scatter plots of the variables in relation to the principal components and individual characteristics.

Table 2. Spatial pattern dimensions represented by principal components.

Principal Component	Spatial Pattern Indicators	Cumulative
pc_1	Gray space scale and monocentricity	0.352
pc_2	Gray space shape complexity and fragmentation	0.536

Table 2. Cont.

Principal Component	Spatial Pattern Indicators	Cumulative
<i>pc</i> ₃	Gray space compactness	0.634
<i>pc</i> ₄	Green space fragmentation and scale	0.709
<i>pc</i> ₅	Green space connectivity	0.774
<i>pc</i> ₆	Green space compactness	0.822

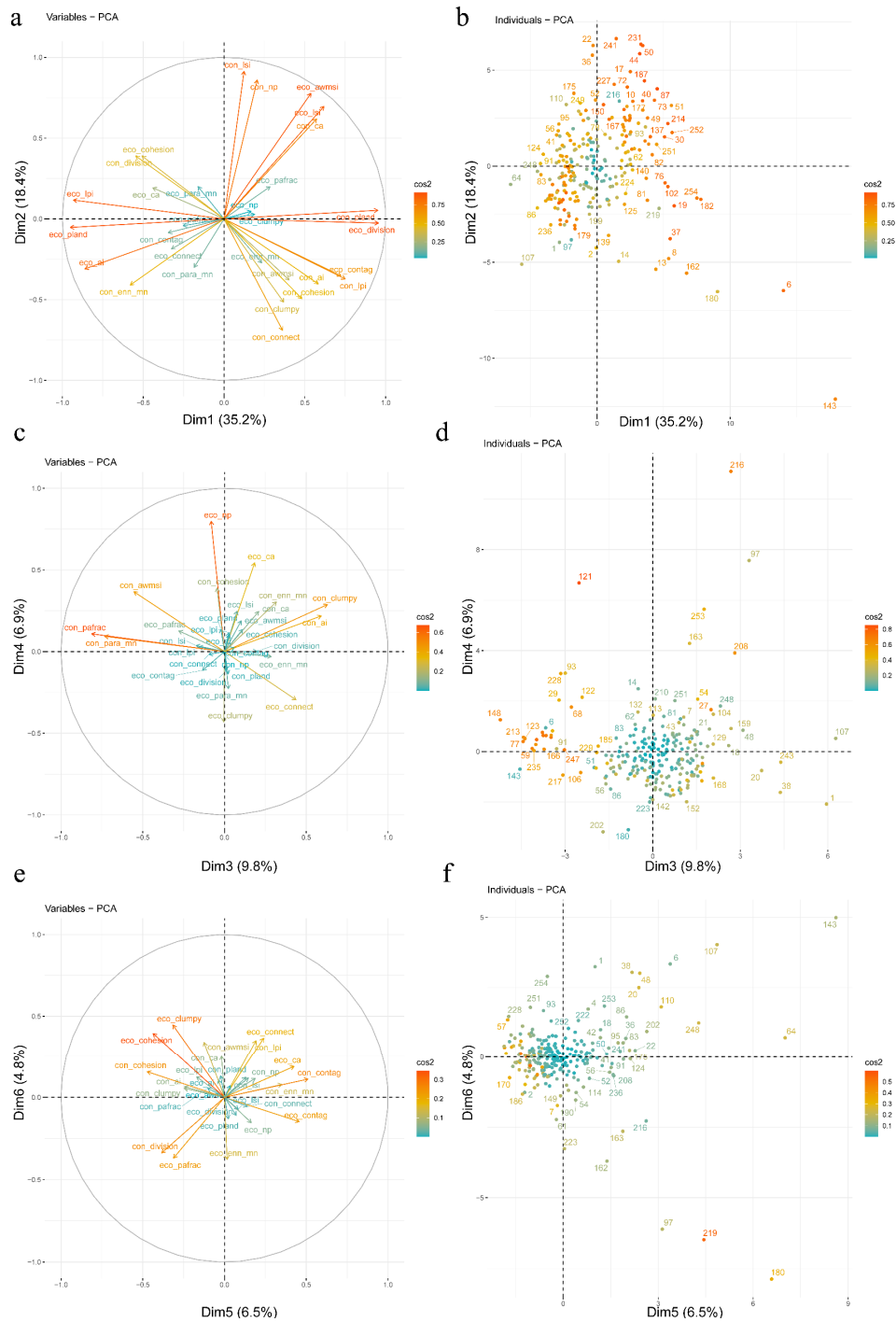


Figure 2. Variable contribution of principal components pc_1 – pc_6 and individual role scatterplot. Note: (a,b) variable contribution of principal components pc_1 – pc_2 and individual role scatterplot, (c,d) variable contribution of principal components pc_3 – pc_4 and individual role scatterplot, (e,f) variable contribution of principal components pc_5 – pc_6 and individual role scatterplot.

2.4.4. Urban Functional Mixing Degree

While the previous section used landscape pattern indices to describe the gray–green spatial pattern of the city, these indices do not capture the internal composition of the urban space. Further refinement is needed to account for the arrangement and combination of spaces within the city. Urban spaces, such as residential areas, office buildings, schools, hospitals, shopping malls, and parks, influence the intensity of population flow and commuting patterns. The layout and distribution of these spaces affect population movement at different times, and the frequent interactions between people can facilitate the spread of diseases like COVID-19. Therefore, the composition and mixing of urban functional areas play a crucial role in the transmission of the virus. Points of Interest (POIs) data provide detailed information about the functional units within the city, which helps to characterize the spatial distribution of these functions [68]. By analyzing POIs, we can gain insights into how different areas within the city are utilized and interconnected. The concept of information entropy, originally used in physics to measure system complexity and equilibrium, can also be applied to cities as a system. In this context, the city's structure and layout can be seen as a spatial representation of this system. The level of information entropy can reflect the degree of balance of urban land use: the higher the entropy value, indicating that the number of land use types of different functions is greater, the smaller the difference in the area of each functional type, and the more balanced the land distribution. When the area of each land use type in the city is equal, the entropy value reaches the maximum, indicating that the urban land use reaches a balanced state. By incorporating the information entropy model, we can quantitatively analyze urban functional areas and their degree of mixing [69].

Specifically, based on POI data, we construct an information entropy model to measure the degree of urban functional mixing. Assuming that the total number of POI data is A and categorized according to different functional categories (e.g., transportation land, recreation, residential land, accommodation services, public administration and public services, hospitals, schools, tourist attractions, food and beverage services, business facilities, living services, shopping service facilities, etc.), there are a total of n categories ($n = 12$). The number of POIs in each category is $A_1, A_2, \dots, A_n$, satisfying $A = A_1 + A_2 + \dots + A_n = \sum_{i=1}^n A_i$ ($i = 1, 2, \dots, n$). If we define the proportion of each category as $P_i = A_i/A$, then the formula of information entropy H is as follows:

$$H = -\sum_{i=1}^N P_i \times \log P_i \quad (9)$$

where $H \geq 0$ and higher values of H indicate that the more functional types are indicated, the smaller the difference in the number of each functional type.

Additionally, using information theory and fractal theory, we introduce the information dimension method to reflect the spatial form of urban function mixing. This approach allows us to extend the study of urban functions through fractional dimension analysis.

2.5. Data Resource

COVID-19 pandemic data for this study were obtained from the official websites of the National Health Commission of the People's Republic of China and the Beijing Municipal Commission of Health. Population migration data were sourced from the Baidu Migration Data Platform (<http://qianxi.baidu.com/> (accessed on 23 May 2023)). These data, derived from Baidu's Huiyan technology, track the movement trajectories of millions of domestic mobile phone users, providing valuable insights into inter-regional population migration. This study used data from 10 January to 1 March 2020, which includes information on migration origin, destination, time, and scale. The migration

scale reflects the total number of people migrating in or out of a city on a given day. Given the typical 7–14 day incubation period for COVID-19, the scale index for urban migration was analyzed during two periods: 10–23 January (before the Spring Festival) and 8–25 February (after the Spring Festival). Land use data for 2020 were obtained from the raster dataset (<https://www.resdc.cn/> (accessed on 3 June 2023)) provided by the Institute of Geographic Sciences and Natural Resources Research, CAS (<https://www.resdc.cn/> (accessed on 5 June 2023)). This dataset, with a 30 m resolution, is currently one of the most accurate land use remote sensing products in China and plays a critical role in national land resource surveys and ecological studies. Based on the “Land Use Status Classification Standard” (GB/T 21010-2017; Current land use classification. China Land Surveying and Planing Institute, Department of Cadastral Management, Ministry of Land and Resources: China, Beijing, 2017), land types were categorized into two broad groups for this analysis: ecological landscape land (green space), which includes arable land, forest land, grassland, and wetlands, and urban land (gray space). Variable statistical descriptions are detailed in Table 3.

Table 3. Variable statistical descriptions.

Dimension	Variable Name	Symbol	Description	Unit
Socio-economic	COVID-19 incidence rate	Covi	Confirmed cases/City's annual average population in the specified time period	%
	Wuhan migration outflow scale index	lnwhq	Population outflow before Wuhan lockdown	/
	Inter-city migration intensity	lnimin	Inter-city population migration volume	/
	Intra-city travel intensity	lnicin	Intra-city travel intensity	/
	Population density	lnpopd	Permanent population/ Administrative area of the city	cases/km ²
	Public budget expenditure	lnpbe	Local government expenditure on various activities in the region	10,000 RMB
	Number of hospital beds	lnnhb	Number of hospital beds in the city	number
	Road density	lnroads	Total road length/ Administrative area of the city	km/km ²
	Education level	lnedu	City's expenditure on the education sector	10,000 RMB
Ecological environment	Daily average temperature	lntem	Average temperature during the specified time period	°C
	Precipitation	lnpre	Average precipitation during the specified time period	mm ³
	Wind speed	lnwind	Average wind speed during the specified time period	m/s
	Air pollution level	lnPM _{2.5}	Average PM _{2.5} concentration during the specified time period	µg/m ³

Table 3. Cont.

Dimension	Variable Name	Symbol	Description	Unit
Spatial form	Gray space scale and monocentricity	pc_1	Indicator derived from principal component analysis	/
	Gray space shape complexity and fragmentation	pc_2	Indicator derived from principal component analysis	/
	Gray space compactness	pc_3	Indicator derived from principal component analysis	/
	Green space fragmentation and scale	pc_4	Indicator derived from principal component analysis	/
	Green space connectivity	pc_5	Indicator derived from principal component analysis	/
	Green space compactness	pc_6	Indicator derived from principal component analysis	/
	entropy	$\ln entropy$	Urban functional mixing degree	/

Note: Population flow data were obtained from Baidu Map Huiyan (<https://qianxi.baidu.com/#/>) (accessed on 23 May 2023)), socio-economic data were obtained from the 2021 China Urban Statistical Yearbook, and land use, temperature, precipitation, wind speed, and air pollution data were obtained from National Earth System Science Data Center, CAS (<https://www.resdc.cn/>) (accessed on 10 June 2023)).

3. Results and Discussion

3.1. Population Mitigation, Habitat Quality, and Urban Land Use Mixture

Before the Chinese New Year, first-tier cities and provincial capitals were the primary sources of population migration, with significant outflows into third-tier urban areas, which typically export large numbers of laborers. The Beijing–Tianjin–Hebei, Yangtze River Delta (YRD), and Pearl River Delta (PRD) regions were the main sources of migration. However, the YRD had a notably wider regional influence (Figure 3a). The role of these metropolitan areas in the spread of outbreaks is particularly critical, with cities of different sizes and their levels of economic development having a significant impact on the path and speed of outbreak transmission. Among these metropolitan areas, the population migrating from Beijing mainly flowed into Hebei, with the number of people moving from Beijing to Hebei before the New Year being roughly four times higher than those heading to provinces like Henan and Shandong. For the super Tier 1 cities (North, Shanghai, Guangzhou, and Shenzhen), population flows are characterized by a strong spatial agglomeration effect, mainly to neighboring provinces and regions. In the YRD and PRD, migration patterns reflected a gradual decrease in population flows with increasing spatial distance, displaying a smoother distribution. Shanghai’s out-migration predominantly flowed into neighboring provinces such as Jiangsu, Anhui, Zhejiang, Henan, and Jiangxi. Similarly, Shenzhen and Guangzhou saw major outflows to Hunan, Guangxi, Jiangxi, Hubei, and Henan. These concentrated trends in migration flows illustrate the radiative power of super Tier 1 cities as economic centers, where strong economic attraction can lead to the large-scale movement of people, which may exacerbate the risk of outbreak transmission, especially in areas of intense economic activity within metropolitan areas. Notable strengthening hotspots were found in the Chengdu–Chongqing urban agglomeration and the lower Yangtze River Delta, while persistent hotspots remained around the Beijing–Tianjin–Hebei, YRD, and PRD urban agglomerations (Figure 3b). These regions are at a high risk for the spread of

the epidemic due to their high level of economic activity and population movement. In contrast, cold spot areas were primarily in the inland northwest region, where population movement is low, economic development is relatively lagging, and the risk of outbreak transmission is low.

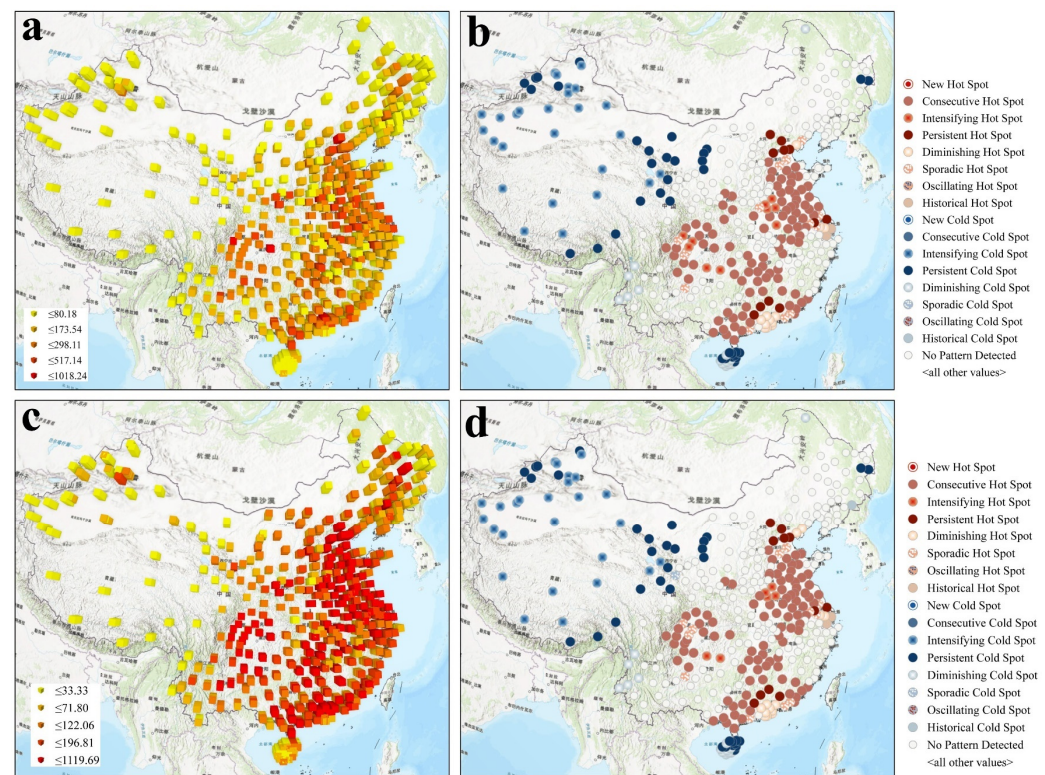


Figure 3. (a) Trend analysis of spatial and temporal distribution of emigrants and (b) analysis of emerging spatio-temporal hotspots of emigrants from 10 January to 23 January. (c) Trend analysis of spatial and temporal distribution of emigrants and (d) analysis of emerging spatio-temporal hotspots of emigrants from 8 February to 22 February.

After the Spring Festival, small- and medium-sized cities became the primary sources of China's migrant workforce (Figure 3c), with significant outflows from third-tier cities to major urban centers like Beijing, Shanghai, Guangzhou, Shenzhen, and provincial capitals. During this period, the migration pattern of the population in third-tier cities, on the other hand, showed a tendency to concentrate more towards first-tier and provincial capital cities. Nearly 10% of the population migrating from third-tier cities moved to first-tier cities such as Beijing, Shanghai, Guangzhou, and Shenzhen, while another 20% moved to provincial capitals within their own provinces. Around 10% of the population migrated to provincial capitals in other provinces, 30% moved to other prefecture-level cities within the same province, and 20% migrated to prefecture-level cities in different provinces. This migration trend reflects the strong attraction of super Tier 1 cities and provincial capitals as centers of labor concentration, and this pattern may have a profound impact on the spread of the epidemic, which is likely to be faster in these areas due to their high population density, well-developed transportation, and high level of economic activity. Tier 1 and Tier 3 cities have the strongest links with each other, a phenomenon that reflects the economic differences between cities and the direction of population movement. The linkages are weaker with second-tier cities, which include all municipalities, provincial capitals, and planned cities outside of the Beijing, Shanghai, Guangzhou, and Shenzhen regions. The risk of epidemic transmission may be more pronounced in these inter-city linkages, especially in regions with concentrated economic activity and high population mobility. Hotspots

of intensified and sustained migration were found mainly around the periphery of the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta urban agglomerations, which are the primary sources of labor export (Figure 3d). In this process, the size of the city, its level of economic development, and its urbanization will directly affect the speed and extent of the spread of the epidemic. Larger cities, with their high concentration of economic and social activities, may become the core areas for the spread of the epidemic. Understanding the characteristics of population movement before and after the Spring Festival is essential for effectively managing outbreaks, especially in order to strengthen surveillance and prevention efforts in hotspots of population movement.

Wuhan's closure began on 23 January, effectively halting the population outflow. We analyzed the trend of population movement during the 14 days leading up to the closure, from 10 January to 23 January (Figure 4). On 10 January, although the majority of the population still flowed into the surrounding areas of the province, there were notable links to major cities like Beijing, Chongqing, Shanghai, Zhengzhou, Guangzhou, Shenzhen, and Hefei. By 23 January, just before the city's closure, the outflow of population had significantly decreased, with movement now largely confined to the nearby peripheral areas. Intra-city travel intensity, measured by the ratio of daily intra-city trips to the city's resident population, serves as an indicator of local mobility. Intercity mobility is a key factor in the spread of outbreaks, particularly when individuals leave Wuhan and move within the local city, coming into contact with the local population. People carrying the virus within the city may then spread it further through their travels, accelerating the epidemic's transmission. Thus, intra-city travel intensity plays a crucial role in influencing the spread of the virus. As shown in Figure 4, travel intensity is notably higher in the Southeast Coastal region, particularly in cities that function as logistics and transportation hubs, which experience more frequent movement.

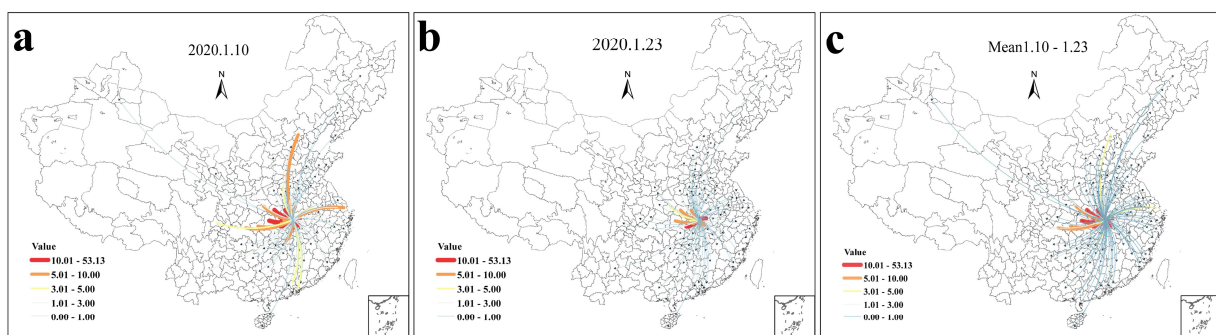


Figure 4. Value of migration from Wuhan to other cities from 10 January to 23 January and mean value of migration from Wuhan to other cities from 10 January to 23 January.

3.2. Dynamics of COVID-19 During Initial Period in China

We employed spatio-temporal cube modeling to examine the spread of COVID-19, utilizing this 3D geo-visualization method to map spatio-temporal data into cubes. This approach is effective in uncovering spatio-temporal patterns. In this model, bars representing different time steps within the same spatial location form a bar time series, while bars distributed across different spatial locations within the same time period create a time slice. During the outbreak phase (Figure 5a), the number of daily new diagnoses increased rapidly, especially in areas surrounding Wuhan. Modern transportation networks facilitated closer inter-city connections, with the Beijing–Tianjin–Hebei, Yangtze River Delta, and Pearl River Delta urban agglomerations being strongly linked to Wuhan. This proximity increased the risk of infection and contributed to the swift spread of the epidemic. Cities like Harbin, Xiamen, and Fuzhou also exhibited stronger connections to Wuhan, further

accelerating the virus's transmission. The cumulative number of confirmed cases reflects this trend (Figure 5b). In cities with close interconnections, any public safety outbreak should prompt immediate emergency measures in nearby cities to prevent further spread.

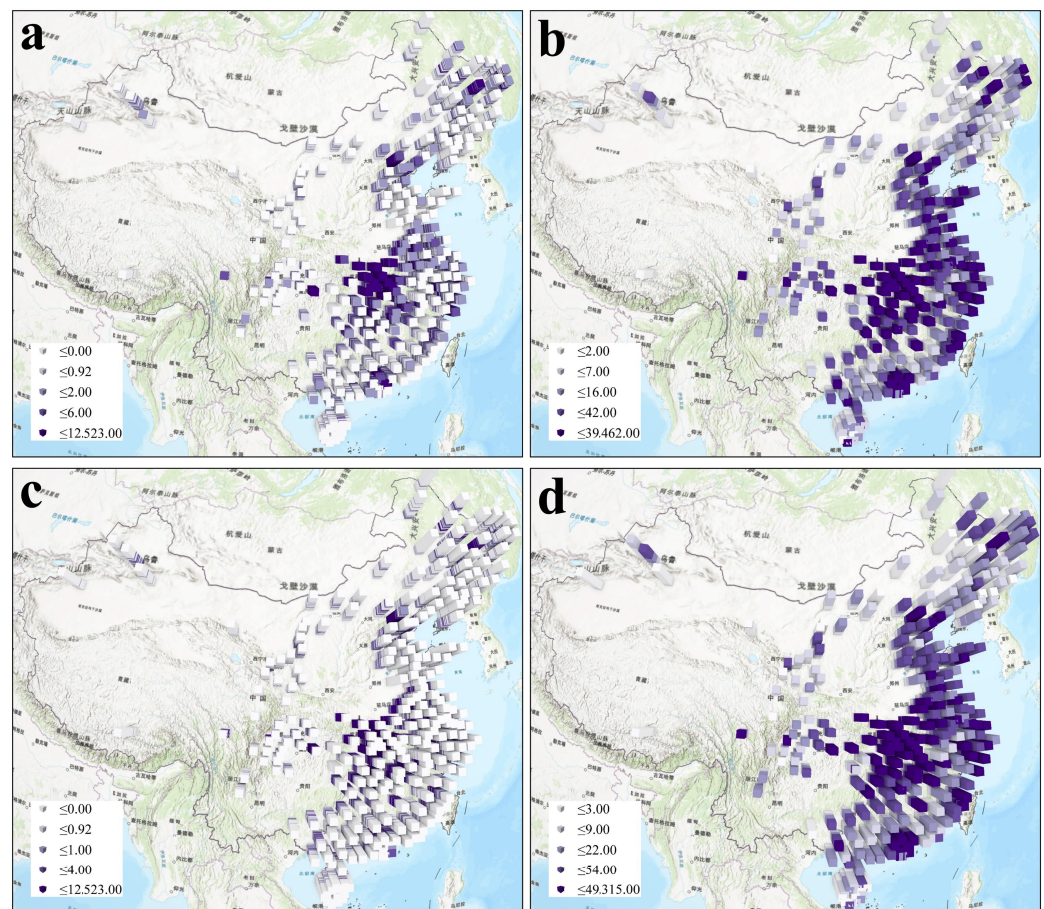


Figure 5. Spatial and temporal spread of new confirmed cases (a) and cumulative confirmed cases (b) from 23 January to February. Spatial and temporal spread of new confirmed cases (c,d) and cumulative confirmed cases from 13 February to 1 March.

During the control and recession phase (23 February–1 March), spatio-temporal cube modeling reveals a clear trend of rapidly decreasing daily new confirmed cases (Figure 5c). Most cities shifted to a white color, indicating minimal new cases, with the exception of Hong Kong, which remains marked in blue. This suggests that the outbreak was largely controlled. The cumulative number of confirmed cases also mirrors this trend, with the spatial distribution reflecting the phase of control (Figure 5d). High-incidence areas were primarily located in Hubei Province and its surrounding regions. Notably, some northeastern areas, such as northern Heilongjiang Province, also exhibited relatively high incidence rates. Conversely, Inner Mongolia and much of Guizhou experienced lower prevalence rates. Overall, the highest COVID-19 prevalence was concentrated around Wuhan, along the southeastern coast, and in parts of northeastern China. In contrast, northern cities and western inland areas showed generally lower infection rates compared to the southeastern coastal regions.

The standard deviation of the ellipse effectively illustrates the spatial spread of COVID-19 over time, highlighting both the extent and directional distribution of the outbreak. As shown in Figure 6, the spread initially expanded rapidly before beginning to decrease. The most significant expansion occurred between 20 January and 26 January, as the outbreak spread quickly across the country. Despite the Wuhan city closure on 23 January, the timing

of the Spring Festival, combined with the prior outflow of people from Wuhan to other cities (potentially carrying the virus), and the typical 7-day incubation period, led to a concentrated outbreak during this period. Following the city closure, migration was halted, and nationwide quarantine policies were implemented to restrict movement between cities. These measures gradually controlled the spread, resulting in a reduction in the spatial extent of the outbreak. The standard deviation ellipse overall shows a northeast–southwest direction, reflecting the concentration of confirmed cases in the southeastern coastal regions, which were more severely impacted by the virus.

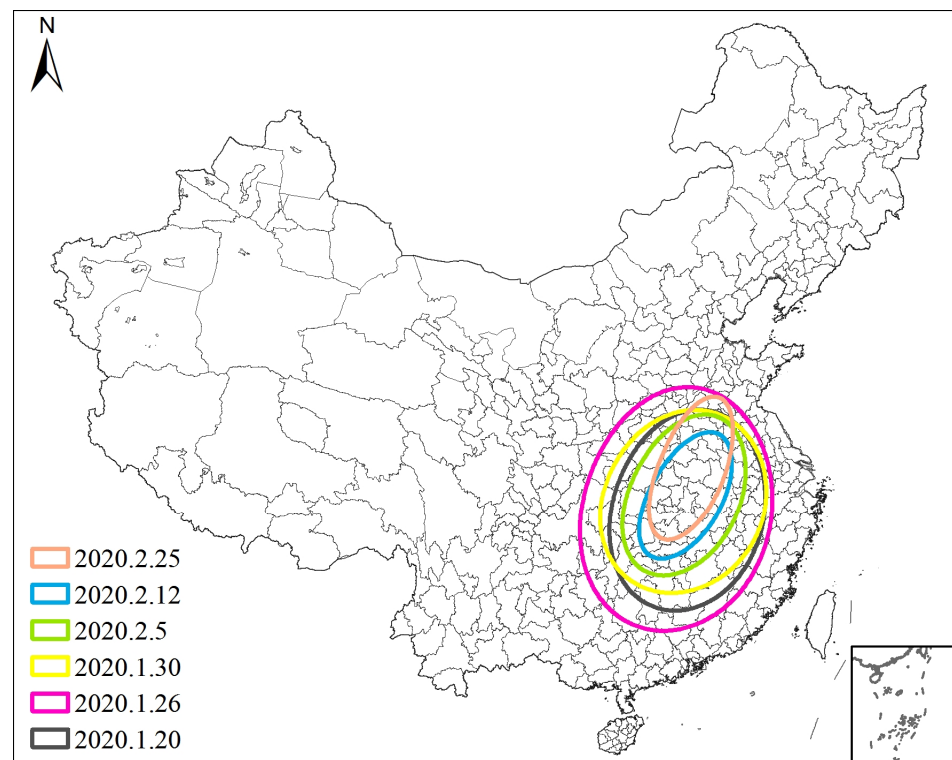


Figure 6. Spatial–temporal distribution of the confirmed patients in China during the initial period (from 20 January 2020 to 25 February 2020).

3.3. Basic Multiple Variables Regression Results

Before multiple regression analysis, it is necessary to check the multicollinearity between variables and exclude variables with large covariance. The multicollinearity test found that the variance inflation factor (VIF) of inter-city migration intensity and the number of hospital beds were 16.42 and 15.26, respectively, which were significantly larger than 10, and therefore could not be included in the regression model (Table 4). Inter-city migration intensity, Wuhan out-migration scale index, and intra-city travel intensity are all reflective of the intensity of population mobility and may be highly correlated, and the spread of COVID-19 is mainly due to the out-migration of the population from Wuhan, and so $\ln_{imin}$ is excluded. For public budget expenditures and the number of hospital beds, both reflecting the local government's resistance to epidemic risk, there is also a high correlation, and $\ln_{nhb}$ is excluded through the VIF.

Table 4. Test results of multiple regression equations.

Variables	Standardized Coefficient (Beta)	T	Significance	VIF
(Constants)	0.121	0.357	0.721	1.256
lnwhq	0.779	14.102	0	2.666
lnimin	0.175	−1.979	0.249	16.42
lnicin	0.102	−2.347	0.02	1.662
lnpopd	0.002	0.044	0.965	1.185
lnpbe	−0.395	2.237	0.026	4.231
lnnhb	0.048	0.456	0.649	15.26
lnedu	−0.256	−1.384	0.068	3.954
lnroads	0.003	0.052	0.959	3.4
lnem	0.046	0.553	0.581	6.025
lnpro	−0.071	1.655	0.099	1.627
lnwind	0.004	−0.092	0.927	1.536
lnPM _{2.5}	0.088	−1.253	0.012	4.274
pc ₁	0.007	0.092	0.926	4.348
pc ₂	0.042	0.762	0.447	2.636
pc ₃	0.01	0.208	0.835	1.997
pc ₄	−0.038	−0.822	0.412	1.818
pc ₅	−0.018	−0.446	0.056	1.437
pc ₆	0.104	2.349	0.22	1.708
lnentropy	−0.006	−0.164	0.87	1.32
adj_R ²	0.62			

3.4. Spatial Spillover Effects of Pandemic and Gray–Green Space Form

First, we tested the spatial correlation between the dependent and independent variables using the global Moran's I and assessed the spatial dependence using the Lagrange multiplier test (LMerror, LMlag, and its robust forms R-LMerror and R-LMlag), and the results are shown in Table 5. The results of the LM test (LMerror, LMlag) indicated the existence of significant spatial dependence ($p < 0.05$), but could not directly distinguish between SLM and SEM. Further robust LM tests (Robust-LM-lag and Robust-LM-error) were equally significant, suggesting that both SLM and SEM may be applicable. To accurately select the model, we analyzed the significance of the spatial lag and spatial error terms using the Wald test and LR test. The results show that Wald-spatial-lag and Wald-spatial-error as well as LR-spatial-lag and LR-spatial-error are significant ($p < 0.05$), indicating that both the spatial lag and error terms cannot be ignored. This implies that spatial dependence in the data may not be adequately captured using only SLM or SEM [70]. SLM is applied to the spatial autoregressive effect of the dependent variable, while SEM is mainly used for the spatial correlation of the error term, and neither of them is able to capture the spatial spillover effect of the explanatory variables. In contrast, the spatial Durbin model (SDM) simultaneously portrays the spatial lag effect of the dependent variable and the spatial spillover effect of the explanatory variables, which is more in line with the spatial characteristics of epidemic spread. Given that the spread of the epidemic is not only influenced by neighboring cities, but also factors such as urban gray and green spatial patterns, which may have spillover effects on the surrounding areas, the SDM can provide a more comprehensive portrayal and make the estimation results more robust. Based on the results presented in Table 6, the fixed-effect SDM was finally adopted in this study to ensure the reliability of the model estimation.

Table 5. Suitability test results of spatial econometric model.

Test Methods	Z Statistics	p Values
LM-lag	25.36 ***	0.001
Robust-LM-lag	112.32 ***	0.001
LM-error	253.62 ***	0.000
Robust-LM-error	389.56 ***	0.000
Wald-spatial-lag	22.36 ***	0.002
Wald-spatial-error	19.56 ***	0.001
LR-spatial-lag	21.96 **	0.001
LR-spatial-error	20.69 **	0.002
Hausman	56.23 **	0.001

Note: *** represents $p < 0.001$, ** represents $p < 0.005$.

Table 6. Spatial regression results of SDM model for COVID-19 infection.

Variable	Coefficient	p Value	Variable	W·Coefficient	p Value
Constant	−3.62	0.19			
lnwhq	1.49	0.00 ***	W·Lnwhq	0.47	0.00
lnicin	0.42	0.02 **	W·Lncncx	0.21	0.01
lnpopd	0.05	0.58	W·lnpopd	−2.37	0.12
lnpbe	−0.73	0.04 **	W * Lndfzc	1.50	0.81
lnedu	−0.15	0.64	W * Lnedu	−0.25	0.97
lnroads	0.23	0.15	W * Lnroads	−5.70	0.11
lnpre	−0.02	0.59	W * Lnpro	−0.53	0.11
lnitem	0.08	0.01 ***	W * lnitem	0.03	0.15
lnwind	0.19	0.55	W * lnwind	−3.68	0.57
lnPM _{2.5}	0.05	0.01 ***	W·Lnpm _{2.5}	0.08	0.03
pc ₁	0.04	0.27	W·pc ₁	0.06	0.02
pc ₂	−0.01	0.89	W·pc ₂	−0.62	0.27
pc ₃	−0.02	0.7	W·pc ₃	0.43	0.55
pc ₄	−0.04	0.4	W·pc ₄	0.28	0.80
pc ₅	−0.07	0.03 **	W·pc ₅	−0.12	0.04
pc ₆	0.03	0.62	W·pc ₆	2.48	0.16
lnentropy	0.28	0.50	W·lnentropy	1.37	0.36
ρ	0.45	$p < 0.05$			
R ²	0.76	$p < 0.01$			
Hausman	20.12	$p < 0.01$			
LR_SLM	125.59	$p < 0.01$			
LR_SEM	161.24	$p < 0.01$			
LMlag	6.02	$p < 0.01$			
LMerror	2.02	$p < 0.01$			
SLM_Wald	36.60	$p < 0.01$			
SEM_Wald	5.24	$p < 0.01$			

Note: ***, **, and * indicate 1%, 5%, and 10% confidence levels, respectively.

Considering that the direct effects and spatial lag coefficients (spatial spillover effects) derived from the spatial Durbin model above do not fully capture the decomposition of spatial effects, we applied a partial differential equation decomposition method to further quantify the direct and spatial spillover effects in the local area. This approach allowed us to obtain a more accurate breakdown of the direct effects and spatial spillover impacts of each influencing factor. The specific results of this analysis are presented in Table 7.

Table 7. Decomposition of the direct, indirect, and total effects of explanatory variables on COVID-19 infection.

Variable	Direct Effect	<i>p</i> Value	Indirect Effect	<i>p</i> Value	Total Effect	<i>p</i> Value
lnwhq	0.732	0.000 ***	0.497	0.027 **	1.228	0.052
lnimin	0.350	0.006 ***	0.101	0.015 **	0.421	0.086
lnpopd	0.010	0.902	0.016	0.94	0.026	0.92
lnpbe	0.926	0.126	1.080	0.193	2.006	0.478
lnedu	−0.645	0.241	−0.739	0.221	−1.384	0.507
lnroads	−0.056	0.729	−0.094	0.89	−0.150	0.842
lnpre	0.020	0.479	0.012	0.796	0.032	0.63
lnitem	−0.092	0.415	−0.140	0.794	−0.232	0.692
lnwind	0.225	0.422	0.312	0.757	0.536	0.638
Lnpm _{2,5}	0.035	0.104	0.016	0.023 **	0.051	0.050
pc ₁	0.015	0.648	0.027	0.015 **	0.042	0.770
pc ₂	−0.002	0.944	−0.014	0.905	−0.017	0.903
pc ₃	0.027	0.477	0.036	0.785	0.064	0.673
pc ₄	−0.030	0.509	−0.030	0.785	−0.060	0.662
pc ₅	−0.044	0.02 **	−0.030	0.007 ***	−0.074	0.079
pc ₆	0.115	0.028 **	0.120	0.55	0.235	0.280
lnentropy	0.02	0.961	0.074	0.924	0.089	0.923

Note: *** and ** indicate 1% and 5% confidence levels, respectively.

From the results of the spatial Durbin model, the variable *lnwhq*, representing the impact of the out-migrating population from Wuhan, shows a local direct effect that passed the significance test at a 1% level ($p < 0.01$), with a coefficient of 0.73. This suggests that the outflow of population from Wuhan significantly promotes the spread of COVID-19, making it the most influential factor among those that passed the significance test. Previous research has focused on two main aspects: the role of population mobility in the spread of the epidemic and the relationship between demographic factors and infection and mortality rates. Population mobility is widely recognized as a critical factor influencing the spread of infectious diseases. Studies using spatial visualization and statistical analysis models consistently agree that population mobility accelerates epidemic transmission [71,72]. Specifically, the outflow of people from Wuhan has been identified as a major factor in the number of cases reported in various locations. As such, the restriction of population mobility through the “city closure” of Wuhan played a key role in the rapid and effective control of the epidemic. Intercity population mobility serves as a primary pathway for cross-city transmission and is a central factor shaping the spatial and temporal dynamics of the epidemic. While the aforementioned studies highlight the role of population as the carrier of the virus, which increases the risk of transmission through contact, they did not explore the spatial spillover effects of population mobility. Our results, however, reveal that $W * \lnwhq$, representing the spatial spillover effect, also passed the 5% significance test ($p < 0.05$), with a coefficient of 0.50. This suggests that the out-migrating population from Wuhan not only directly impacted the local spread of the epidemic, but also induced a positive spatial spillover effect, further promoting the spread in neighboring areas. This is largely due to the speed and convenience of modern transportation, which has enhanced connectivity between cities through an extensive network of roads, high-speed railways, and other modes of transport. The increased population movement facilitated by these transportation networks resulted in rapid population flow between cities. As the out-migrating population from Wuhan reached their destination cities, they contributed to extensive contact with local populations. These individuals, in turn, could spread the

virus to other neighboring cities through the intercity transportation network, leading to the swift transmission of the outbreak in those areas.

The local direct effect of $\ln_{\text{imin}}$, which represents the intensity of intra-city travel, passes the 5% significance test ($p < 0.05$) with a coefficient of 0.35. This suggests that higher intra-city travel intensity promotes the spread of COVID-19. While the out-migrating population from Wuhan plays a significant role in epidemic transmission, local intra-city travel also facilitates the spread of the virus. As people move within the city, they are likely to come into close contact with others through various forms of transportation and daily activities, contributing to the local spread of the epidemic. Additionally, the spatial spillover effect, $W * \ln_{\text{imin}}$, also passes the 5% significance test ($p < 0.05$), with a coefficient of 0.10. This indicates that intra-city travel intensity not only directly influences the spread of the epidemic within the local area, but also has a positive spillover effect, promoting epidemic transmission in neighboring areas. This is primarily due to the high intensity of intra-city travel and increased population mobility, which increases the likelihood of virus-carrying individuals coming into contact with a larger portion of the population. As these individuals move across regions and cities, they potentially spread the virus to neighboring areas, further accelerating the transmission of COVID-19.

In terms of spatial patterns, pc_5 , which represents green space connectivity, demonstrated an inhibitory effect on the spread of COVID-19. It passed the 5% significance test ($p < 0.05$) with a local direct effect coefficient of -0.04 , indicating that higher green space connectivity helps reduce the spread of the virus. The spatial lag coefficient, $W * pc_5$, also passed the significance test ($p < 0.05$) with a coefficient of -0.03 , suggesting that green space connectivity not only inhibits local outbreaks, but also plays a role in controlling the spread of the virus in neighboring areas. This result highlights the importance of maintaining and improving green space connectivity, which contributes to ecological health, biodiversity, and social distancing. Green spaces act as ecological corridors, preserve habitats, and provide open spaces for urban residents, which can act as refuges or evacuation sites during public health crises, such as the rapid construction of square cabin hospitals during the COVID-19 pandemic. In contrast, Pan et al. found that green spaces with high connectivity are more likely to be transmission nodes due to the concentration of crowd flow paths, which positively contributes to the spread of the virus [73]. For this reason, we believe that it is the difference in study scales that leads to the difference in results. Our study focuses on the prefecture-level city scale in China, which spans a large geographical distance. In contrast, the study by Pan et al. [74] focuses on London boroughs, which are smaller in scale and more densely populated than our study area. Despite the connectivity of green spaces, as population density exceeds a certain threshold, the evacuation capacity of green spaces is limited, which, in turn, contributes to disease transmission.

In contrast, pc_1 , representing the scale of gray space and monocentricity, did not pass the local significance test, indicating that it did not have a direct effect on the epidemic's spread. However, $W * pc_1$ passed the 5% significance test ($p < 0.05$) with a coefficient of 0.03, indicating a positive spatial spillover effect, promoting the spread of COVID-19 in neighboring areas. This result reflects the role of highly urbanized monocentric cities with expanded infrastructure, dense buildings, and road networks, which increase population mobility and inter-city connections, thereby accelerating the virus's transmission. This finding is the same as that of Abozeid et al. [75]. On the contrary, in the case of a polycentric city, when a central area is infected, it is possible to isolate that area from the rest of the city by isolating the transportation links between that area and the rest of the city, with the rest of the central area acting as the main driving force of the city to sustain the city's development, and by this method the further spread of infectious diseases can be effectively suppressed without interrupting the city's development.

Unlike previous studies like [76,77], which found no significant relationship between green space and health outcomes, our study highlights the spatial spillover effects of green space patterns on COVID-19, showing that green space connectivity can not only reduce local outbreaks, but also prevent the spread of the virus in surrounding areas. Furthermore, our analysis of gray–green spatial patterns provides a deeper understanding of how spatial layouts impact the spread of infectious diseases, enriching the theory that urban spatial structures influence epidemic dynamics.

In order to demonstrate the impact of these spatial distributions more clearly, we supplemented the analysis of the compactness and sprawl of gray and green spaces with a graphical representation. Figure 7 demonstrates the compactness of green space, with looser compactness, slower urbanization, and relatively less infrastructure in the northwest, while the Southeast Coastal region limits the expansion of green space due to rapid urbanization and dense gray infrastructure. Figure 8, on the other hand, illustrates the spreading of green space, which is better in the Northeast, Northwest, and Southwest regions, while regions such as the Southeast Coast and the Shandong Peninsula limit the spreading of green space due to high population densities and building intensities. Similarly, the compactness (Figure 9) and spreadability (Figure 10) of gray space show regional differences, especially in first-tier and provincial capital cities, where compactness of gray space is higher and spreadability is lower.

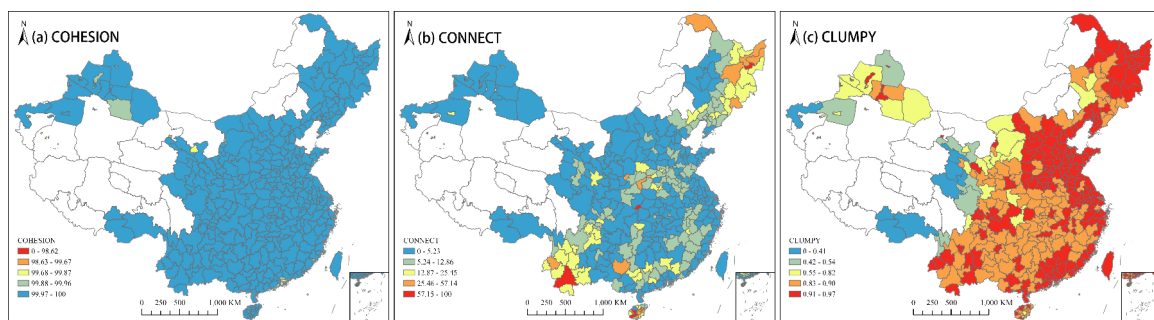


Figure 7. Green space compactness. Note: (a) green space cohesion, (b) green space connectivity, (c) green space clumpiness.

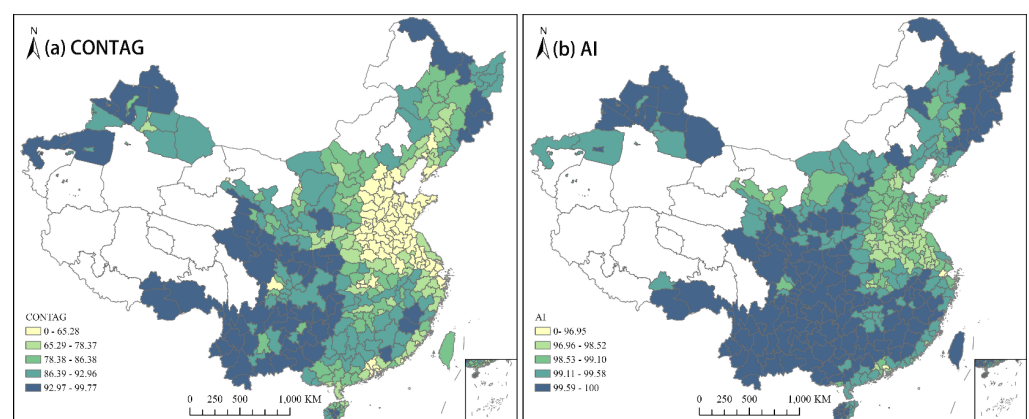


Figure 8. Spreadability of green space. Note: (a) green space contagion, (b) green space aggregation index.

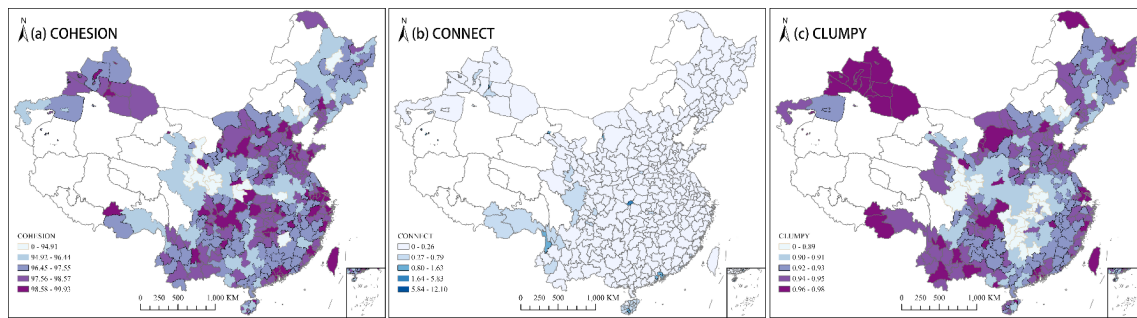


Figure 9. Compactness of gray space. Note: (a) gray space cohesion, (b) gray space connectivity, (c) gray space clumpiness.

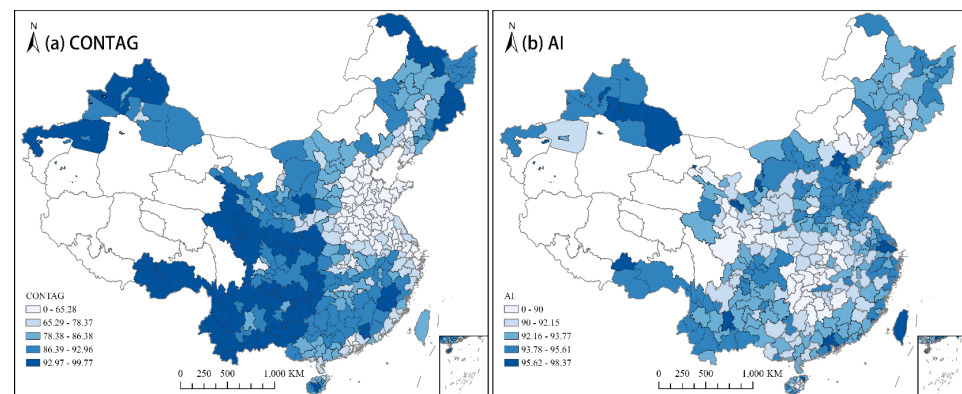


Figure 10. Spreading of gray space. Note: (a) gray space contagion, (b) gray space aggregation index.

In terms of ecological factors, the natural environmental variables such as mean daily temperature, precipitation, wind speed, and $PM_{2.5}$ had relatively small overall effects on the spread of COVID-19. Intem, which represents the effect of mean daily temperature, did not pass the significance test, and $W * Intem$ also did not show significant results, so these variables will not be discussed in detail. In terms of ecological factors, the natural environmental variables such as mean daily temperature, precipitation, wind speed, and $PM_{2.5}$ had relatively small overall effects on the spread of COVID-19. Intem, which represents the effect of mean daily temperature, did not pass the significance test, and $W * Intem$ also did not show significant results, so these variables will not be discussed in detail. Additionally, $W * lnpm_{2.5}$, the spatial spillover effect of $PM_{2.5}$, also passed the 5% significance test ($p < 0.05$) with a coefficient of 0.02. This indicates that air pollution not only affects the spread of the epidemic within the local area, but also produces a positive spillover effect, promoting the spread of COVID-19 in neighboring areas. $PM_{2.5}$ is known to be transported and dispersed by atmospheric flow, with a long diffusion distance and a wide range of influence [19]. While the local direct effect and spatial spillover effect of $PM_{2.5}$ may appear to be small, the broad range of its impact makes it an important factor for authorities to consider, especially given the long-distance transport and diffusion of $PM_{2.5}$ particles.

4. Policy Recommendation

Based on the research results, we propose the following optimization strategies to address the spread of COVID-19 while guiding the sustainable development of cities. These suggestions focus on three key areas: “Control”, “Connect”, and “Guide”, which aim to improve epidemic prevention by enhancing the interaction and integration between urban ecosystems and socio-economic systems.

“Control”: managing uncontrolled urban development and protecting ecological landscapes. As urbanization progresses, the urban fringe often experiences ecological degradation, leading to the loss of green spaces and ecological corridors. Urban planning should establish clear boundaries to prevent unchecked expansion, ensuring a balance between urban growth and the preservation of the natural environment. Green space connectivity has been shown to play a critical role in controlling the spread of epidemics. According to the Several Opinions on Further Strengthening the Management of Urban Planning and Construction document, it is clearly stated that the urban development boundary should be delineated, urban ecological restoration should be strengthened, and the natural landscape pattern of the city should be protected. Cities should prioritize the protection and restoration of ecological landscapes. These measures will help maintain ecological integrity and support the sustainable development of urban ecosystems. The construction of green buildings and infrastructure should be a priority. Utilizing low-carbon and environmentally friendly materials and design concepts will reduce the negative impacts of urbanization on the environment. The Green Building Evaluation Standards provide clear norms and guidelines for green building design, construction, and operation. At the same time, increasing the accessibility of public green space not only helps improve public health, but also reduces the risk of disease transmission. According to the outline of the “Healthy China 2030” Plan, it is proposed that healthy cities should be built and the number of urban green spaces and other elements of a healthy environment should be increased, which provides policy support for the construction of urban public green spaces. Additionally, increasing the availability of public green spaces can improve public health by reducing disease transmission risks.

“Connect”: improving the connectivity of green spaces and promoting ecological networks. Planning and developing multiple green corridors within and around the city is vital. These ecological passages connect different green spaces and natural environments, promoting biodiversity and reducing fragmentation. The National Ecological Functional Zoning Plan emphasizes the importance of ecological corridor construction in maintaining regional ecological integrity and biodiversity. Protecting existing corridors and restoring damaged ones will enhance the city’s green infrastructure and support healthier urban ecosystems. Green spaces play a significant role in improving the urban microclimate through transpiration, reducing air pollution, and lowering PM_{2.5} concentrations. Under the Action Plan for Continuous Improvement of Air Quality, an increase in the area of urban greenery is proposed to improve urban air quality. Enhancing greenery in cities will not only contribute to the overall health of urban ecosystems, but also reduce the risk of airborne diseases, making cities more resilient to future pandemics.

“Guide”: rational land use planning for the harmonious development of gray and green spaces. Urban planning should clearly delineate areas for residential, commercial, and public green spaces. The creation of ecological buffer zones between different land use types will help prevent excessive development and ecological degradation. The Urban Blue Line Management Measures provide a policy basis for the protection of ecologically sensitive areas, such as urban waters, and its concepts can be used to set up ecological buffer zones in urban planning. Sustainable urban development depends on the effective integration of gray infrastructure (e.g., buildings, roads) and green spaces. Planning should focus on enhancing the functionality of green spaces, increasing their ecological and social value. This could involve incorporating more public green areas into urban designs, providing residents with spaces for recreation, leisure, and social interaction, while also promoting the city’s ecological health. The Standard for Planning and Design of Urban Residential Areas puts forward clear requirements for the allocation of green space in residential areas, etc., which can be used as a reference for the functional construction of

urban green space. Cities should aim to create a harmonious balance between gray and green spaces. This can be achieved by focusing on the sustainable development of both infrastructure and green areas, ultimately creating urban environments that are resilient to public health risks.

The spread of COVID-19 is not confined to individual cities. Intercity connectivity and spatial spillover effects play a significant role in the epidemic's spread. To enhance epidemic prevention efforts, cross-regional coordination is essential. Cities should strengthen collaboration by sharing information and resources related to epidemic prevention. According to the Guiding Opinions on Improving the Institutional Mechanism for Prevention and Control of Major Epidemics and Improving the Public Health Emergency Management System, it is proposed that a sound mechanism for the joint prevention and control of major epidemics should be established and strengthened to provide coordinated regional prevention and control. In urban agglomerations with intensive traffic flows, an inter-regional coordination mechanism should be established to facilitate joint epidemic prevention measures. In addition to epidemic control, cities should collaborate to protect regional ecological corridors and green space resources. This will help avoid ecological fragmentation and enhance the ecological resilience of the region. The Guiding Opinions on the Establishment of a Nature Reserve System with National Parks as the Mainstay emphasizes the importance of building regional ecological networks and provides policy support for the protection of inter-city ecological corridors. By improving the connectivity of large-scale ecosystems, cities can create a stronger ecological foundation for effective epidemic control.

5. Conclusions

In this study, we adopted a comprehensive approach to understanding the spatial dynamics of COVID-19 spread in cities by focusing on three key dimensions: socio-economic factors, ecological environment, and spatial form. Using principal component analysis (PCA), we quantified the gray-green spatial pattern of cities through landscape pattern indices and represented population mobility through the Baidu Migration Scale Index. The STRIPAT and spatial Durbin models were employed to assess the role and spatial spillover effects of key influencing factors on the epidemic. Based on these analyses, we proposed optimization strategies for urban gray-green spatial structure to better control the spread of COVID-19. The main findings of the study are as follows. The out-migration from Wuhan and the intensity of intra-city travel had a significant local impact on COVID-19 spread. These factors not only contributed to local transmission, but also exhibited positive spatial spillover effects, spreading the virus to neighboring areas. This highlights the importance of controlling population mobility in epidemic prevention efforts. Green space connectivity (pc_5) was found to significantly inhibit both local and neighboring epidemic spread. This supports the idea that well-connected green spaces, which serve as ecological corridors, can help reduce the spread of diseases by enhancing urban biodiversity and providing space for social distancing during epidemics. This aligns with the growing understanding of the importance of green infrastructure in urban health. In contrast, the spatial scale and monocentricity of urban areas (represented by pc_1) were found to increase epidemic spread in neighboring cities. This finding suggests that urbanization, characterized by dense infrastructure and high mobility, facilitates disease transmission. $PM_{2.5}$ (air pollution) demonstrated both direct and spatial spillover effects on the spread of COVID-19. The higher the concentration of $PM_{2.5}$, the more it promoted the spread of the virus locally and in surrounding areas. This underscores the dual role of air pollution as both a carrier of the virus and a factor exacerbating its transmission.

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