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The urban infection susceptibility index and its application in cities of China

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ABSTRACT

Infectious diseases pose a serious threat to human health and social safety. In order to better respond to large-scale outbreaks of infectious diseases in the context of climate change, it is essential to identify potential high-risk areas in cities. However, there is currently a lack of a standardized metric or indicator for quantifying the potential risk of urban infectious diseases. The main objective of this study is to construct an urban infection susceptibility index (UISI) to identify and quantify susceptibility risk, thereby providing insights for constraining and prevent future epidemics. The UISI considers both human activities (population density, closeness index, betweenness index, life service, functional synthesis indicator, hospital accessibility) and climate-related factors (temperature, particulate matter 2.5, wind speed, humidity), and is specifically designed to analyze potential high-risk areas of urban epidemics across cities worldwide. The index integrates a wide range of factors based on the criteria importance obtained through the intercriteria correlation method, producing fine-scale susceptibility maps at the urban grid level. We apply the UISI to the coronavirus disease 2019 risk assessment in Lanzhou and Shanghai, which has been well verified. This UISI is both easy and effective to calculate across various cities, providing a scientific basis for rapid policy-making and implementation to prevent the spread of infectious diseases. Furthermore, we predict the UISI trends across different shared socioeconomic pathways (SSP), specifically SSP5-8.5 and SSP2-4.5, which demonstrate an increasing trend from 2025 to 2100.

1. Introduction

Infectious diseases have posed a significant threat to human health, directly impacting social and economic development [1]. Despite significant substantial achievements in the prevention and control of infectious diseases, the risk of unpredictable infectious diseases still exists [2]. In recent years, the frequency of large-scale outbreaks has increased significantly. In March 2020, the outbreak of coronavirus disease 2019 (COVID-19) was officially declared a global pandemic [3]. Furthermore, on July 23, 2022, and August 14, 2024, the World Health Organization (WHO) declared the Mpox outbreak a global public health emergency [4]. Climate change also represents a major threat to human health. In 2019, WHO officially listed climate change as one of the top ten threats to global health. Global warming has greatly influenced the distribution of vector organisms and will affect the outbreak and spread of many infectious diseases [5]. C. Mora et al. [6] found 58 % (218 out of 371) of infectious diseases have been aggravated by climate change. Furthermore, future scenarios suggest that both newly emerging and severe infectious diseases could be exacerbated under continued climate change [7,8].

Environmental and climatic factors have been confirmed to affect the transmission of infectious diseases, especially respiratory diseases [9,10]. J. Xie and Y. Zhu [11] explored the relationship between mean temperature and confirmed cases in 122 cities in China during the COVID-19 pandemic. They found that mean temperature has a positive linear relationship with the number of confirmed cases when temperatures are below 3 °C;. Some studies have also pointed out that COVID-19 was driven by seasonality factors, with transmission decreasing during the summer period [9,12,13]. In addition, humidity also influences the transmission of epidemics. Many scholars have used models to analyze the relationship between relative humidity and daily new COVID-19 cases, and found a negative correlation between relative humidity and the number of cases [14–16]. Y. Diao et al. [17] observed that high maximum temperature and absolute humidity reduce the spread and decay periods in some countries. There is also evidence that the virus can be transmitted *via* droplets and airborne routes [18], drawn more attention to the association between air pollution and epidemic transmission. Under low relative humidity conditions, the moisture in virus-containing droplets rapidly evaporates, forming droplet nuclei that stay in the air for a longer period of time,

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HIGHLIGHTS

Scientific question

Infectious diseases remain a major challenge to global public health and sustainable urban development. However, the fine-scale impacts of human activity and climate change on urban infection susceptibility have not yet been quantified.

Evidence before this study

Under the influence of climate change, about 58 % of known infectious diseases in humans are becoming increasingly threatening, with the total number of affected infectious diseases exceeding 200. The simultaneous occurrence of climate change and infectious diseases constitutes a serious compound health crisis; how to accurately identify potential high-risk areas of infectious diseases is urgently needed.

New findings

This study constructed a general urban infection susceptibility index (UISI) that firstly considers both human activities and climate change to predict potential high-risk areas of infectious disease outbreaks. We applied UISI on the prediction of risk areas of coronavirus disease 2019 in Lanzhou and Shanghai, which achieved good results.

Significance of the study

This study provides an innovative approach for identifying and analyzing the high susceptibility risk areas of urban infectious diseases. The urban infection susceptibility index effectively captures the main influencing factors of epidemic spread, demonstrating high accuracy and reliability, providing a scientific basis for timely policy formulation and implementation of response measures to infectious disease outbreaks.

thereby increasing the likelihood of pathogen transmission [19,20]. A. Srivastava [21] reviewed the relationships among COVID-19, air pollution, and meteorology conditions, summarizing that air pollution and the number of infected cases were positively correlated and that wind played some role in the spread of the virus. M. Coccia [22–24] revealed that the transmission of air pollution to human might be strengthened under low speed wind, and low exposure to air pollution could reduce fatality rate. However, environmental and climatic factors may have opposite effects at different altitudes and latitudes [9,25]. Environmental and climatic conditions in high-altitude and low-altitude areas may have different impacts on the spread of infectious diseases.

Cities serve as the primary spaces for human residence and interaction. Factors such as the built environment, air pollution, and climate have been shown to affect respiratory infections in urban areas [26]. People living in large cities often have higher levels of social interaction [27,28]. Convenient urban transportation systems meet the basic mobility needs of urban population and create an ideal condition conducive to the spread of infectious diseases [29,30]. The transmission of infectious disease in cities is also affected by policies and human behavior. Under strict lockdown policies (e.g., in China), epidemic durations can be shortened [17]. Vaccines are crucial tools in pandemic response and protection against severe diseases. In the initial phase of an epidemic outbreak, rapid vaccination can reduce its negative impact on human safety [31]. Some scholars have summarized lessons from COVID-19, pointing out that the increase in healthcare expenditures and vaccine production can reduce the spread of epidemics [32,33]. In addition, high average health expenditures in the health sector and per capita can help mitigate the fatality rate [23]. International mobility trends are also critical determinants of COVID-19 spread, sometimes even more important than population and climate facotrs, which cannot be ignored [34].

Facing the future challenge of unknown epidemics, an effective early warning system can ensure the timely detection and reduction of suspected cases [35]. One of the main early warning approaches focuses on identifying potential high-risk areas for infectious disease outbreaks. M. Sun and X. Jiao [36] proposed a comprehensive identification method, that successfully determined the risk level of epidemic distribution in Harbin. K. Imdad et al. [37] used the actual number of COVID-19 cases, along with socioeconomic, demographic, and climatic factors to construct the susceptibility index. They classified five schemes to visualize district-level susceptibility risk in India. M. Coccia [38] also proposed that the Index c (as contagions) contains air pollution, atmospheric stability, population density, and respiratory disorders to indicate exposure risk to infectious diseases in Italy. H. Ren et al. [39] employed the Maxent model to identify the potential risk zones in China's megacities. In their study, the confirmed cases and nine socioeconomic factors were gridded by the densities on the 1 km × 1 km scale to calculate the index.

Analyses of susceptibility risk area are important for identifying likely high-incidence areas and populations that may be affected, thus preventing epidemic outbreaks and diffusion. Human activity factors may play a significant role in an epidemic where environmental and climatic factors differed slightly in the city. Therefore, by integrating the effects of human and climatic factors, key characteristics of susceptibility to infectious diseases can be better captured. Meanwhile, constructing a fine-scale susceptibility index can help policymakers identify environmental weaknesses of urban areas in terms of exposure

Table 1
Comparison between UISI and susceptibility index proposed by other studies.

Variables	M. Sun, X. Jiao [36]	M. Coccia [38]	H. Ren et al. [39]	UISI
Society factor	Road, POI, Heat map data Building	Population density, Respiratory disorders of people	Epidemic data, Population, Mobility data, POI data, Hospital data	Population, Road data, POI data, Hospital accessibility
Climate factor	_	Air pollution, Wind speed	_	Temperature, $PM_{2.5}$, Wind speed, Humidity
Resolution	500 m × 500 m	Cities level	1 km × 1 km	1 km × 1 km
Method	Entropy weighting method	Ranking	Maxent model	CRITIC method

Abbreviations: UISI, urban infection susceptibility index; POI, points of interest; CRITIC, criteria importance obtained through the intercriteria correlation.

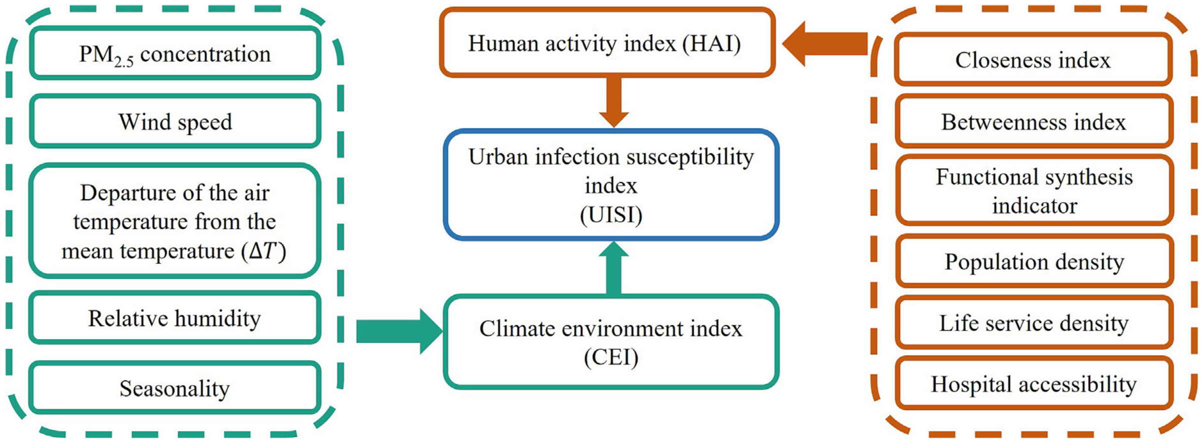

Fig. 1. Diagram of the urban infection susceptibility index. Abbreviation: $PM_{2.5}$, particulate matter 2.5.

to infectious diseases and thereby support epidemic prevention. However, there are still gaps in identifying the susceptibility index. Some researchers have combined human and climate factors to conduct the index on the scale of a district or country, which is not precise enough on the spatial scale [37,38]. Other scholars have constructed the index in the grid of fine scale, but they used only human activity factors, neglecting the influence of climatic factors [36,39]. Obviously, there is currently no uniform susceptibility index that simulataneously considers both human activities and climate change and is suitable for assessing the potential risk of urban infectious diseases at a fine scale (Table 1).

Therefore, the primary objectives of our study are to address the gap in identifying epidemic susceptibility risk at a fine scale by: (1) constructing an urban infection susceptibility index (UISI) at a fine-scale that combines both human activity and climatic influence (Fig. 1); (2) assessing the accuracy of UISI using COVID-19 data; and (3) projecting future UISI trends in the context of climate change.

2. Materials and methods

2.1. Proposed index

In this paper, UISI was proposed as a new method to quantifies susceptibility risk to infectious diseases at a fine grid scale by jointly incorporating human activity and environmental-climatic factors. The UISI valuses were divided into four levels, including low, moderate, high, and very high. The higher the level of UISI, the greater the exposure risk and the higher the morbidity in the regions.

2.2. Parameters

Population density (POP) was used as a parameter. It was collected from the WorldPop (https://hub.worldpop.org/), which was at a spatial resolution of 1 km.

Another parameter enclosed was closeness index (network quantity penalized by distance in radius hybrid [NQPDH]). It represented the convenience of reaching other roads within the search radius. The larger of the NQPDH value, the more attraction to urban populations.

$$NQPDH(x) = \sum_{y \in R_x} \frac{W(y)P(y)}{d(x,y)} \tag{1}$$

In formula (1), R referred to the search radius (1 km in this study). x and y denoted the road segments, and $d(x,y)$ was the shortest distance between them. $W(y)$ was the weight of road y. $P(y)$ represented the proportion of road y within R. In the discrete space, the $P(y) = 1, y \in R_x; P(y) = 0, y \notin R_x$.

Betweenness index (two-phase betweenness hybrid [TPBTH]) represented the probability of choosing a certain section of road in the shortest possible way within a certain search radius. As of the following formula (2), the $OD(x,y,z)$ represented the shortest path connecting road x ,y, and z; N was the collection of all road segments; R referred to the search radius. Total weight(y) was the total weight of all paths starting from road y. $P(z)$ was the proportion of z within the radius R; $W(z)$ represented the weight of z.

$$TPBTH(x) = \sum_{y \in N} \sum_{Z \in R_x} OD(x,y,z) \frac{W(z)P(z)}{totalweight(y)} \tag{2}$$

Points of interest (POI) represented specific places where people conduct daily activities. The number of POI of life service represented Life service density (LSD).

Functional synthesis indicator (FSI) was a quantified indicator designed to evaluate the functional diversity and integrity of urban areas. It measured the concentration and interaction of different urban functions in each regions. FSI contained 14 types of POI (Supplementary data). The larger the FSI, the higher the functional integration of the region. The calculation formulas for FSI was as follows.

$$P_k^m = \frac{A_k^m}{\sum_{m=1}^{M} A_k^m} \tag{3}$$

$$FSI^m = -\sum_{k=1}^{14} P_k^m \times \log P_k^m \tag{4}$$

Poor hospital accessibility (HACC) was associated with larger outbreak of epidemic, including higher morbidity and mortality rates [27,28,36]. Thus, we collected 1 km scale hospital accessibility to quantify the ability of cities to respond to infectious diseases [40].

Extreme weather and air pollution were crucial factors influencing the outbreak and spread of infectious diseases. X. Lian et al. [41,42] found that both heat waves and cold waves could accelerate the transmission of infectious diseases. We collected the 1 km-resolution monthly temperature data [43–46] and calculated the anomaly of the temperature from the climatic mean as influencing factor. In addition, particulate matter 2.5 ($PM_{2.5}$) concentration at 1 km resolution [47,48], wind speed, and relative humidity were also used as factors assessing exposure to the environment [49,50].

The 1 km multi-scenario, multi-model monthly temperature dataset for China (2021–2100) was provided in the National Qinghai-Xizang Plateau Data Center [43,44,46,51]. The dataset included three shared socioeconomic pathway (SSP) scenarios (SSP1-1.9, SSP2-4.5, SSP5-8.5). SSP1-1.9 assumed that more and more people will turn to sustainable development practices, SSP2-4.5 assumed a moderate emission pathway, and SSP5-8.5 model assumed a socio-economic pathway with heavy reliance on fossil fuel energy.

The data of medium–high-risk areas were obtained from the State Council Client Mini Program. Epidemic data on COVID-19 infected cases in Lanzhou City were obtained from the Lanzhou Municipal Health Commission (https://wjw.lanzhou.gov.cn/) including the locations and report dates of comfirmed cases. We collected infected cases and medium–high-risk areas data in Lanzhou City during the COVID-19 outbreak to estimate the COVID-19 risk index. In order to reflect both the location of positive individuals and the general characteristics of infection, we aggregated the risk areas data and positive infected cases data according to a weight coefficient of 7:3 to construct the COVID-19 risk index (Supplementary data).

2.3. Data analysis procedure

Firstly, we estimated the human activity index (HAI), which on the basis of six human indicators: NQPDH, TPBTH, FSI, POP, LSD, and HACC. The HAI was defined as follows:

$$HAI = w_1 NQPDH + w_2 TPBTH + w_3 FSI + w_4 POP + w_5 LSD + w_6 HACC \tag{5}$$

The indicator weights $w_i(i = 1, 2, \cdots, 6)$ were determined according to criteria importance obtained through the intercriteria correlation (CRITIC) method (Supplementary data).

Secondly, the $PM_{2.5}$ concentration, ΔT, wind speed, and relative humidity were used to build the climate environment index (CEI). Most studies have shown a negative correlation between relative humidity and the daily number of new COVID-19 cases, so we inverted relative humidity in formula (6). In addition, we considered the effect of seasonality on the transmission of epidemic, which is learned from X. Liu et al. [12]. The CEI was calculated by the following formula (6):

$$CEI = \frac{PM_{2.5}}{wind} \times \Delta T \times seasonality \times humidity^{-1} \tag{6}$$

All human activity indicators and environment-climate indicators were nondimensionalized.

Finally, the susceptibility index values for each grid were obtained using the following formula (7):

$$UISI = HAI \times CEI \tag{7}$$

3. Results

The results of HAI and CEI are displayed in Fig. 2. The HAI values were greatest in Chengguan District, where the population was large and the LSD was high. In these areas, the frequency of human contact and human mobility was higher, which may increase the probability of infectious disease diffusion. In high-risk areas, regular monitoring should be strengthened and control should be emphasized after epidemic outbreaks. The spatial differences in CEI across Lanzhou City were relatively small, with a clear high-value area appearing in Xigu District. There were also some areas in Qilihe District with relatively high CEI values. Qilihe District is a densely populated area in Lanzhou City, and the combination of high POP and the impacts of climate change has inevitably posed a greater risk of infectious disease spread. Therefore, when facing the risk of epidemic outbreaks, it is crucial to prioritize epidemic prevention and control in these areas. On the one hand, monitoring and control should be strengthened and public awareness of self-protection should be raised to prevent the spread of the epidemic. On the other hand, it is necessary to plan the allocation of medical resources to reduce the spread of infectious diseases and other health risks.

The calculation result of UISI is presented in Fig. 3A. We classified UISI into four categories according to the probability density function. The moderate and low levels represented relatively minor influence of human activity and climate change, whereas high-risk level referred to a significant impact of human activity or climate change. In contrast, very-high-level areas represented regions where both human activities and climate change had significant impacts. As illustrated in Fig. 3B, the very-high and high levels of UISI are mainly in the Chengguan District and Xigu District. There is also a very-high-level area in the Honggu District, while other areas have lower susceptibility risks. Similar to the study in Harbin, risk levels gradually decreased from the center to the periphery, mainly because intense human activities provided direct conditions for the spread of infectious diseases [36]. Based on human activities, climate change has further amplified the spread and susceptibility range of infectious diseases. This finding reminds us that it is important to plan the distribution of urban facilities and residential areas in advance, because once an epidemic breaks out, exposure to pollutants may cause widespread transmission of infectious diseases [24]. In Chengguan District, particular attention needs to be paid to the impact of population mobility and the distribution of FSI. During the COVID-19 period, infected cases and medium–high-risk areas were mainly located in Chengguan District. This pattern was closely related to high population aggregation and high-frequency population mobility. In addition, this was also consistent with the distribution of high-level UISI. Therefore, the construction of UISI has allowed us to more clearly distinguish areas with high risk of infectious disease transmission. By implementing early monitoring before the outbreak of an epidemic and timely control after the outbreak, the risk of epidemic spread can be minimized.

The risk index based on the COVID-19 data is shown in Fig. 3C. The distribution of the risk index was mainly concentrated in Chengguan, Qilihe, and Anning District, with the maximum value appearing in

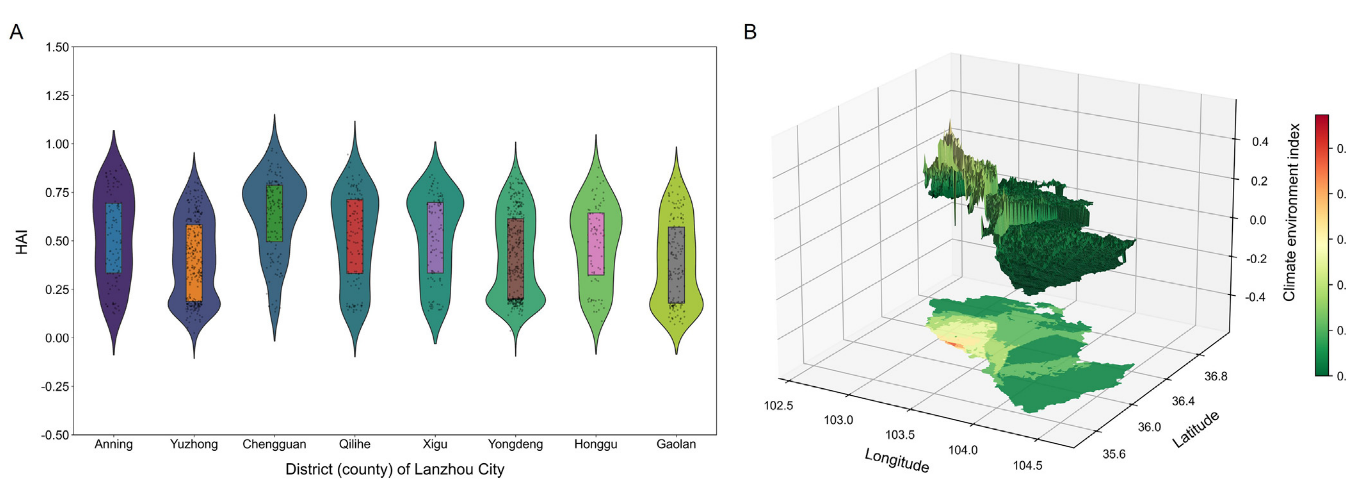

Fig. 2. The distribution of human activity index (A) and climate environment index (B) in Lanzhou City. Abbreviation: HAI, human activity index.

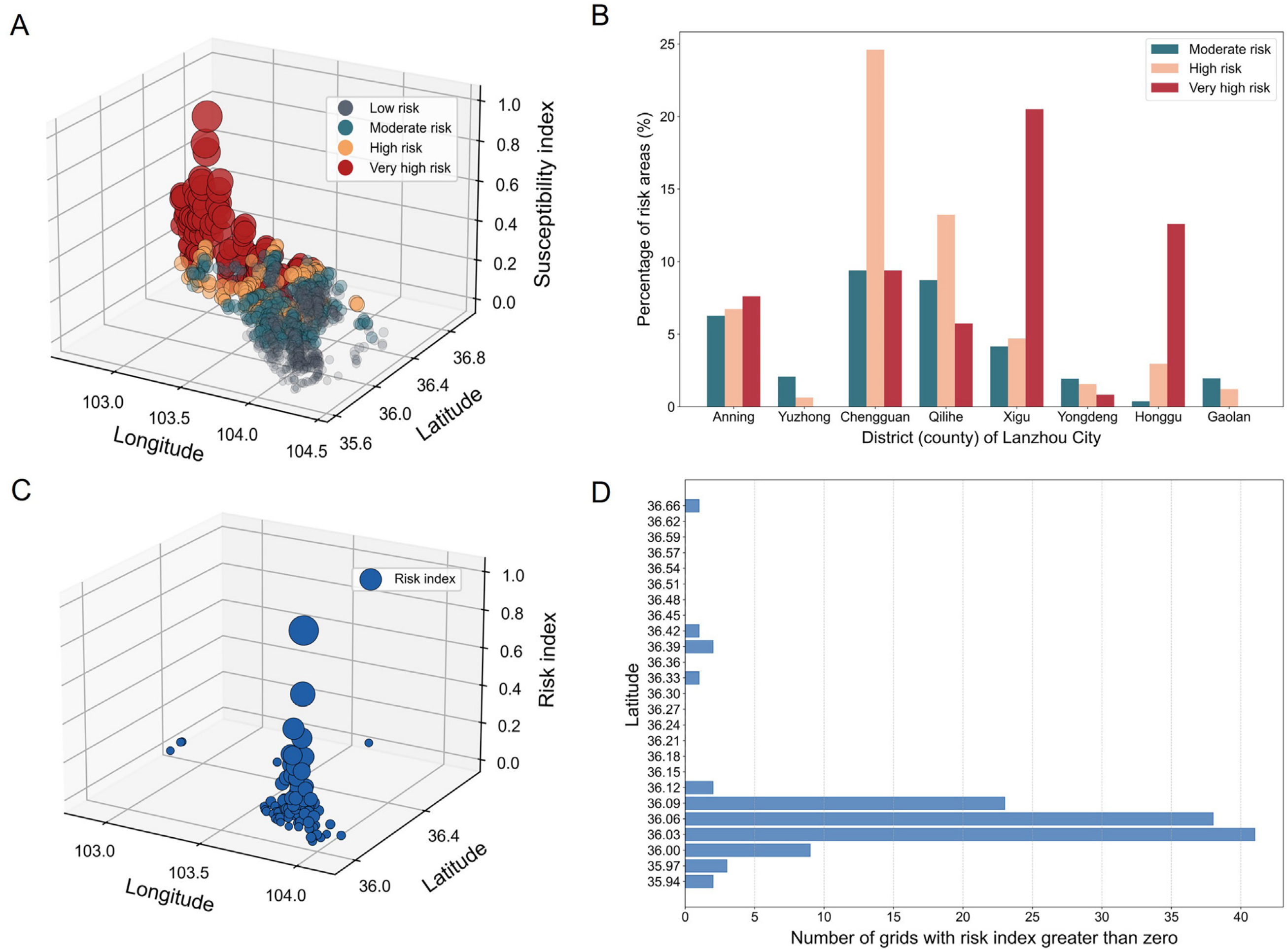

Fig. 3. The distribution of urban infection susceptibility index (A) and the percentage of urban infection susceptibility index aeras in each district (B), the distribution of risk index (C) and the number of risk index regions in Lanzhou city (D).

Chengguan District, where infection was the most severe (Fig. 3D). Due to the rapid development of transportation, the mobility of the population will expand the spread scale. For example, there were areas with low risk value, such as Yuzhong County, where timely control measures prevented more extensive infections.

The clustering distribution of COVID-19 risk values aligns well with the very-high-level area of UISI. By further analyzing areas where infections occurred during the COVID-19 period (areas where the risk index value was greater than zero) under different levels of UISI, we verified our results at a fine-scale grid. A total of 91.3 % of areas with COVID-19 risk were in a higher level of UISI, of which 34.8 % were in the very-high level and 56.5 % were in the high level. The remaining 8.7 % of areas with moderate and low UISI might have been associated with sporadic cases. On account of the rapid development of transportation, the occurrence of infections was somewhat random. UISI mainly reflects the concentration of epidemic diffusion and development; therefore, it accurately predicts high-risk areas of infectious diseases. Before or during infectious disease outbreaks, UISI can provide scientific support for epidemic prevention and control.

Compared with other studies [36–39], UISI considers more factors of human activity and climate, and environment. The compound influence of climate and human activity is reflected in the distribution of UISI. For instance, although the HAI value in Chengguan District is high, the comprehensive value in some parts of Chengguan District is relatively low when the impact of climate factors on transmission is taken into account. In contrast, climate and environmental factors increase the UISI risk level in Yongdeng County. This has reminded us that it is necessary to adopt sustainable development strategies to guide urban development and reduce urban susceptibility risks. In conclusion, although UISI has some limitations in capturing all factors influencing epidemic transmission, especially for epidemic dynamic, it effectively combines climate and human activity to achieve early warning of infectious diseases in the context of climate change.

The UISI trend caused by temperature changes in Lanzhou City from 2025 to 2100 is shown in Fig. 4. In the future, the mechanisms of epidemic outbreak and diffusion may change due to the severe impacts of climate change. Therefore, it is necessary to model the impact of temperature changes on UISI. Under the SSP5-8.5 and SSP2-4.5 scenarios, the average UISI in Lanzhou City demonstrates a monotonic increase trend. This indicates that UISI values will increase and that the area of high and very-high UISI levels will expand, with more regions facing the risk of widespread transmission of infectious diseases. However, under the background of SSP1-1.9 scenario, the overall fluctuation of UISI is not significant, and there is a downward trend in the later period. This means that, under this scenario, not only is the living environment imporved, but the development of infectious diseases is also curbed. Therefore, we need to work together to reduce the trend of temperature change and move towards sustainable development goals. At the same time, it is necessary to plan urban development and infectious disease early-warning efforts in advance, monitor areas with high susceptibility indices, and protect human health.

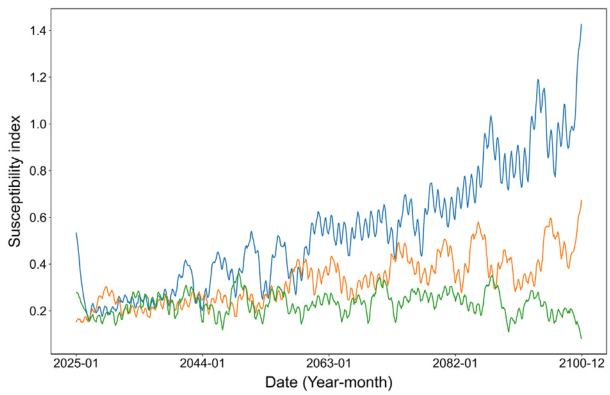

Fig. 4. Prediction of the trend of UISI in the future caused by temperature changes from 2025 to 2100 (blue line: SSP5-8.5 scenario, orange line: SSP2-4.5 scenario, green line: SSP1-1.9 scenario). Abbreviations: UISI, urban infection susceptibility index; SSP, shared socioeconomic pathway.

4. Discussion

On account of the lack of refined grid data on infected cases, we were only able to validate UISI in Lanzhou City and Shanghai (Supplementary data). The validation of UISI in Shanghai further verified the effectiveness and generalizability of the index. In addition, we predicted the UISI trend driven by temperature changes in Lanzhou City from 2025 to 2100. These prediction results have limitations, because the UISI trend was based only on temperature change and thus made a simplification of urban dynamics, including both human activity and climatic factors. Urbanization and climate change can produce complex and interacting effects, and it is difficult to predict all of these processes. Therefore, we only predicted changes in susceptibility risks caused by temperature, with the aim of raising awareness of the impact of climate change on infectious diseases.

Currently, global development is accelerating and the impacts of climate change are intensifying. For example, rapid urbanization and abrupt infrastructural changes in cities may lead to the following consequences: (1) urban expansion: increasing the probability of contact between humans and host animals and increasing POP in areas that originally lay within ecological boundaries, thereby increasing the risk of zoonotic diseases; (2) new transportation hubs: increasing the number of transportation hubs and creating new functional zones, resulting in greater human mobility; (3) urban microclimate: slowing air circulation, exacerbating the urban heat island effect, and increasing urban precipitation, all of which may have positive impacts on the spread of infectious diseases. According to the distribution of UISI, high-level areas are mainly concentrated in the core area of cities and gradually decrease from the center to the periphery. In areas with high building density and low wind speeds, the risk is generally higher [36]. Reducing pollution levels and slowing climate change are crucial for improving public health [21,22,24]. Our predictions of UISI indicated that susceptibility risk will significantly increase substantially with temperature under the SSP5-8.5 scenario. In the future, adopting sustainable urban planning can reduce people's exposure to infectious diseases [38].

In addition, we have found that although the risk of infectious diseases in medium-risk areas was relatively low, it showed an upward trend. Especially in Shanghai, 20.8 % of infections occurred in medium-susceptibility areas. We speculate that this pattern was mainly impacted by transportation convenience. In megacities such as Shanghai, epidemics can spread across the entire city within a single day. In addition, the compounded effects of climate change may further promote the spread of infectious diseases. Greater attention should be paid to the development of spollover risks and to the interactions and transformations among areas of different susceptibility levels. UISI is important for identifying likely high-risk epidemic areas. However, there are also some limitations to this study; the influencing factors involved in UISI are not comprehensive. For example, the reproduction number R value combines real-time infections and deaths and is widely used to monitor epidemic transmission [52]. If more refined observational data become available in the future, we will incorporate R into UISI. Additionally, COVID-19 has proven that the action of a single country is not enough to address a global threat [18,32]. In the future, human health will be closely linked to urban health. We hope that countries worldwide will share data to conduct a unified UISI framework to tackle the compounding crisis of climate change and infectious diseases.

Moving forward, we aim to develop a global UISI and produce a real-time global UISI map displaying the susceptibility risk of cities. Currently, we can leverage our infectious disease diffusion model to provide early warnings of spillover risk for different infectious diseases based on UISI and human mobility. In the future, people may be able to obtain information about the susceptibility risk of their areas in a manner similar to weather forecast. In addition, our index will be applicable to wide range of respiratory infectious diseases. We plan to develop parameterization schemes according to different types of diseases (influenza, dengue fever, and others) to better monitor and warn urban risk of infectious diseases to human health.

In response to the impact of the climate change on infectious diseases, interdisciplinary collaboration among epidemiology, atmospheric science, and environmental science should be strengthened to improve epidemic prediction and early warning. In addition, we will incorporate methods in atmospheric sciences to develop different parameterization schemes for different infectious diseases and different cities, so as to better simulate urban infectious disease risk. An infectious disease prediction model is also crucial for preventing potential epidemics. Since the outbreak of COVID-19, J. Huang et al. [53–55] have developed a global prediction system for the COVID-19 pandemic, which has made great achievements in predicting the epidemic development trends. Currently, our team is developing an infectious disease diffusion model, which is applicable to the diffusion and spread of infectious diseases within cities. The construction of UISI provides the foundation for our parameterization scheme of the diffusion coefficient. In the future, we will further improve the applicability and adaptability of the UISI. Finally, in the context of climate change, we will apply UISI to the multi-model coupling for infectious disease prediction and provide more accurate early-warning information.

5. Conclusions

This study developed a UISI map that simultaneously considered human activities and climate change at a fine urban grid scale, thereby identifying areas with high susceptibility risk. According to the spatial distribution of UISI, our results showed that Chengguan and Honggu Districts exhibit the highest risk of susceptibility. In addition, we collected data on COVID-19 infected cases and medium–high-risk areas and constructed a COVID-19 risk index. UISI was then validated against this COVID-19 risk index with promising results, and 91.3 % of areas with a risk index of COVID-19 are in high and very-high UISI levels, indicating that the UISI we constructed can provide scientific support for the prevention of urban infectious diseases. We further simulated the temporal evolution of UISI from 2025 to 2100 according to temperature changes under the SSP1-1.9, SSP2-4.5, and SSP5-8.5 scenarios. The average UISI increased significantly under the SSP2-4.5 and SSP5-8.5 scenarios, whereas changes were relatively small under SSP1-1.9 scenario. Therefore, greater attention must be paid to urban structure and sustainable climate development strategies to mitigate the impact of climate change on urban infectious diseases. In the context of climate change, the transmission mechanisms of infectious diseases are likely to evolve. Atmospheric sciences have carried out numerical simulation predictions for many years. Strengthening interdisciplinary collaboration between epidemiology and atmospheric sciences can achieve more effective prediction and early warning of urban infectious diseases.

The UISI provides an integrated metric that offers a scientific basis for rapid policy-making and implementation to prevent the spread of infectious diseases. The method proposed in this study is simple and effective for application across different cities. It not only quantifies the relative weights of human activity factors, but also fully integrates human activity and climate-environmental factors to estimate susceptibility risk. In the context of climate change, this method is effective in quantifying climate-related factors and identifying the compound impacts of climate change on infectious diseases.

Nevertheless, UISI has limitations in terms of the indicators considered. Epidemic data and human mobility patterns should be incorporated into UISI to capture the dynamic evolution of epidemic transmission. For example, H. Ren et al. [39] incorporated epidemic data to evaluate the spatiotemporal variations of epidemics. M. Coccia [38] integrated mortality rates for trachea, bronchi and lung cancer to identify population with higher infection risk. Currently, UISI incorporates most of the key factors that influence the spread of infectious diseases and provids ex-ante risk of susceptibility at a fine spatial scale in cities. In the future, we will take into account additional human activity and climate-related factors, including epidemic-specific factor (such as R values, control measures, parameterization scheme of virus, water and sanitation conditions), to better identify and evaluate the susceptibility of cities to future epidemics and to support strategies that mitigate the adverse impacts of infectious diseases on human health. In addition, we will combine UISI with epidemic prediction model to provide more accurate predictive warnings. In conclusion, the UISI proposed in this study not only has important implications for early warning of infectious diseases but also contributes to achieving sustainable development goals in cities.

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Conflict of interest statement

The authors declare that there are no conflicts of interest.

Author contributions

Wei Yan: Writing – original draft, Writing – review & editing, Visualization, Methodology, Data curation. **Jianping Huang:** Writing – original draft, Writing – review & editing, Funding acquisition. **Xinbo Lian:** Writing – original draft, Validation, Formal analysis. **Han Li:** Writing – original draft, Validation. **Shuoyuan Gao:** Validation, Methodology, Data curation. **Shujuan Hu:** Writing – original draft, Writing – review & editing, Funding acquisition.

Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.bsheal.2025.11.002.

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