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Assessing urban resilience to public health disaster using the rough analytic hierarchy process method: A regional study in China

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\section*{A R T I C L E   I N F O}

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\section*{A B S T R A C T}

In the context of frequent occurrences of disasters worldwide, disaster-coping capability is imperative for risk reduction and contemporary emergency management. The global COVID-19 pandemic since 2020 has further highlighted the significance of resilience construction at different geographical scales. Overall, the conceptual cognition of resilience in disaster management covers multiple elements and has diverse yielding on regional assessment. This study assesses the local resilience to the public health disaster in the prefecture-level cities, focusing on two dimensions consisting of vulnerability and capability in the targeted provincial region of Jiangsu in China. To this end, based on the vulnerability-capability framework, the Rough Analytic Hierarchy Process (Rough AHP) method was applied to the resilience assessment. Drawing upon the criteria derived from literature, the criteria weights were determined with the RAHP method and we assessed urban resilience with census data. In addition, the hierarchical factors contributing to urban resilience were determined using robustness analysis. This research provides constructive ideas for regional disaster reduction and contributes to the government's capability to improve urban resilience.

\section*{1. Introduction}

Currently, emergency and multi-hazard disasters have destructive power and widespread range and represent a severe threat to human safety, health, and security. Particularly, some novel and emerging infectious diseases have enormous impacts on people's lives, and sequentially cause morbidity and mortality beyond borders \cite{1,2}. Thus, it is imperative to reduce the risks of all-hazard disasters on population health, which is not only a task for public health services but also a critical necessity for the administration to maintain sustainable development. China, one of the frequently disaster-torn nations, has experienced a variety of public health disasters \cite{3,4} and to a certain extent, has accelerated domestic health policy adjustment, although the effective operation of a response system is challenging. During the 2003 SARS outbreak, China reported 5327 probable cases, of whom 343 died, giving a fatality ratio of 6.4\% and spanned a large geographical extent (170 counties of 22 provinces). More serious public health disasters, such as the ravaging COVID-19 pandemic, have had unprecedented consequences on the nation’s politics, economy, trade, and people's health \cite{5,6}. All along, the public health policy and the implementation of emergency strategy have evolved with China’s domestic reform and national security objective. In general, China’s public health policy is regarded as a critical component of its disaster reduction system, and the urban-rural assessment is critical for uncovering potential loopholes in emergency management. In particular, Communist Party of China has underscored the vital significance of all-round capability construction in providing “public health safety” \cite{7,8} since the COVID-19 outbreak, whereas the reduction of vulnerability and enhancement of resilience is an essential target of national policy tactics in re-framing China’s public health system.

In previous decades, researchers have focused on the perspective of resilience in the disaster management system that can be responsive and proactive to any health disaster threat. Resilience, a core element and common concept of reducing disaster risk, is taken as the prerequisite for managing public health hazards and an essential benchmark for emergency assessment \cite{9,10}. Generally, a resilience system is defined as a flexible structure that could rapidly adapt its actions to changing circumstances and broadly mobilize networks of expertise and any material support for emergency response. Many studies have been conducted on urban and rural resilience to explore how to effectively reduce the damage caused by health-related disasters \cite{11,12}. Also, there have been various attempts to address challenges related to health risks and strengthen governmental capability in the international community.
For instance, the well-known Hyogo Framework for Action 2005-2015 (HFA), *Building the Resilience of Nations and Communities to Disasters*, was adopted by the World Conference on Disaster Reduction [13]. The far-reaching Sendai Framework for Disaster Risk Reduction (SFDRR, 2015-2030), with an emphasis on disaster resilience, was highly endorsed by the UN General Assembly and adopted by nearly 200 countries (or regions) as a 15-year voluntary agreement. The 58th World Health Assembly adopted International Health Regulations (hereinafter “IHR”), which were subsequently implemented in 2007, and all the state parties were required by the IHR to develop certain public health capacities. Besides, the Inter-American Development Bank (IADB) raised an integrated framework for safety assessment and further designed Disaster Risk Management Indicators (DRMI), which is also applicable in the public health disaster-coping context. Many countries, particularly the developed nations, adopted a capabilities-based planning approach and implemented resilience assessment as part of their disaster risk reduction endeavors [14]. For example, the Hazards United States Multi-Hazard (HAZUS-MH) system, developed by the US Federal Emergency Management Agency, is a large GIS-based system for monitoring loss estimations of disasters and implementing risk assessment on various geographical scales [15]. These strategies and frameworks highlighted the importance of national action and collaboration to improve emergency preparedness and reduce potential disaster risks. Their performance was also evaluated under the multi-hazard coupling effects of an earthquake, fire, and infectious disease. However, the scope for resilience rarely addresses the local/regional traits of heterogeneity, including the vulnerability assessment, evolutionary dynamics, and disaster response.

Moreover, comprehensive resilience assessment requires the involvement of various stakeholders’ cognition and participation to incorporate authentic ideas into regional/local assessment. However, stakeholder involvement often results in complex and even conflict preferences [16], which represents a practical challenge for the implementation of assessment. Therefore, the critical issue is how to handle the stakeholders’ perceptions of the weights of assessing factors. In this respect, multi-scale experimental and multi-criteria techniques have been taken as a promising path to determine various indicators since they have the potential to treat multi-dimensional, incommensurable effects of individual decisions. Of these, the most widely used methods include the Analytic Hierarchy Process (AHP), Outranking Theory, and Goal Programming [17-19].

As tentative research, this study constructed the vulnerability-capability analytical framework for regional public health disasters and proposed an integrated approach for resilience assessment using AHP and Rough Set Theory (RST) in the Chinese provincial context. AHP is one of the most widely adopted multi-criteria decision-making methods that is effective in structuring group decisions and manipulating the qualitative criteria. The RST is a mathematical tool capable of dealing with subjective judgments by overcoming the limitations of Fuzzy Set [19,17,20,21]. By integrating the merits of both RST and AHP, the proposed Rough AHP method measures the weights of factors enabling regional resilience to incorporate the preferences of multiple stakeholders. We believe that the constructed approach can promote resilience consensus in the vulnerability-capability framework for managing urban public health disasters. Specifically, we aimed to determine the conditions of dealing with public health disasters at a provincial level and to explore the role that the tendency, if it exists, plays in future urban resilience construction.

In light of this, this study proceeded by collecting panel and survey data in the cities of Jiangsu province. Economic development level and disaster-coping resources of northern, central, and southern areas of Jiangsu, located in Southeast China, vary considerably. It was also one of the key provinces for resilience construction in China toward the modern emergency system. Although relevant studies have been conducted on resilience assessment in the context of disasters, only a few have assessed urban resilience from the public health perspective of regional vulnerability and emergency response capacity. Hence, this research applied an integrated assessment pathway to evaluate urban resilience using the Rough AHP approach that can fully exploit the subjective-objective data. The rest of this paper is organized as follows. Section 2 presents a brief literature review. Section 3 describes the proposed method. Section 4 provides the results and discussion of the regional application using the method. Finally, Section 5 concludes the article.

2. Literature review

For decades, the high-frequency occurrence of public health disasters has been a global phenomenon. Accordingly, the concepts of capability, vulnerability, and resilience are frequently used in scientific literature. A search of the abstract and citation database of Web of Science (WOS) in Sept. 2020 with the query capability yielded over 300,000 results, whereas the keyword of “capability AND vulnerability” combined yielded nearly 11,000 results. Despite various viewpoints worldwide, capability in disaster management is defined as the power of resilience in terms of financial, technical, institutional leadership, and human resources that stakeholders ought to possess to perform emergency actions. The United Nations Office for Disaster Risk Reduction (UNISDR), for example, takes capacity enhancement as a critical target of its agenda [22]. The ability to manage uncertainties or correlated risks (capacity) affects the ability to respond (capability), and it is assumed that disaster preparedness would benefit from including the capacity explicitly in public health emergency response. Houdijk [23] argued that capability stands for possible factors that can positively influence the outcome of disasters and crises. Aven [24,25] proposed the ACU framework that relates the assessment by some definitions of events (A), consequences (C), and uncertainties (U), which we consider critical concerning the capability of public health disaster response. Capability analysis aims to determine which aspect or performance may be the most vulnerable to the hazards and to identify key factors that affect the state of vulnerability [26,22]. The results of vulnerability-capability studies can be used for risk decisions, including risk reduction strategies and disaster mitigation.

Because capability-based assessment of the public health performance is gaining ground in a risk management context, it is common to relate the concept of capability and resilience in an integrated framework and pursue solutions in the world [27-29]. The Coordination Continuity of Operations, produced by the US Federal Emergency Management Agency, included multiple indicators for evaluating vulnerability and capability in organizations [30]. It also introduced a quantitative method by a straightforward analysis of threats to safety, including the public health disaster. Rufat et al. [31] indicated that a key point in measuring vulnerability and capacity to modern hazards is identifying the influencing factors because identified demographic, socioeconomic status, and health are the leading drivers of vulnerability. Furthermore, the Disaster Risk Management Indicators [32], developed by the US National University of Colombia, extended the vulnerability-capability framework to include various categories of disasters. This assessment was applied in different geographical regions [33-35]. Under the UN Development Program of Disaster Reduction (DPDR), the capability-focused assessment and analytical tool of resilience have become a common path in detecting disasters, incorporating the application in the public health domain [36,37]. To explore the regional resilience in the public health disaster context and develop corresponding strategies for risk mitigation, this study constructed the assessment using the vulnerability-capability framework.

In China, recently, researchers have used a likewise or revised vulnerability-capability framework in emergency management [38]. In addition, the administration at different levels established various assessment indicators for China’s public health system. Among these, some notable ones include the “Health Emergency Capacity Evaluation Index” by Chinese Center for Disease Control and Prevention, the “Health Assessment Capacity Assessment Standard” by the National Health and...
Fig. 1. Schematic diagram of the urban resilience assessment in public health disasters.

Family Planning Commission, and the “Competency of Health Emergency in County-level Disease Control Institutions” by the National Health Commission. Generally, these frameworks include multiple dimensions and indicators, such as respond capability, coordination capability, drill capability, and information integration capability. Despite differences, all frameworks have in common vulnerability and capability, which are supposed to jointly affect the health emergency system. For example, Liu [39] proposed a performance-based assessment framework, in which vulnerability and capability are assumed to possess a negative correlated relationship, implying that it could yield a probability of deterioration when the capability of the regional public safety system is weak and vulnerable. Liu [40] suggested four aspects of assessment, namely the natural force, technology, social culture, and legal system in emergency settings, which were applied to specific public health disasters such as the H7N9 infectious disease. Furthermore, threshold (also called “critical value”) is taken as a pivotal target in recognizing the links for disaster management and studies have identified its significance for the evolution of the public health system [38,41]. Some other studies used the technique of simulation or the method of quantitative risk assessment [42,43] as the analytical tool to test the relations.

Although there has been progressing in the theoretical cognition of capability and vulnerability in disaster systems and public health domains over the past decades, the advancement in measuring and assessing its status toward regional resilience is still inadequate. The global COVID-19 pandemic has accelerated the necessity to explore resilience levels in response to sudden public health disasters. It revealed broad differences in the real world, both in China and abroad. Thus, this study’s objective is to describe the essential elements of a resilient public health emergency system using the capability-vulnerability framework and disclose the mutual relationship at extensive provincial levels. For this, this study refined the health emergency assessment indicators to evaluate conditions in sampled cities and provide evidence-based recommendations for resilience construction in terms of public health policy.

The schematic diagram of the design and implementation path is presented in Fig. 1.

3. Materials and method

3.1. Screening and assessment framework

Considering the urban resilience in the context of public health disasters, it is necessary to investigate how significant the urban response is after the disaster occurs, what are influencing factors, and how to assess the recovery conditions in a limited time-space. Also, the assessment of emergencies is essential to support applicable arrangements for subsequent disaster rescue and response. Therefore, to achieve the research goal, we first adopted the “integrated theory-practice” strategy to screen literature for public health indicators, incorporating accessible Chinese academic journals, government gazettes, statistical files, and documents from the sampled regions. A comprehensive search of Chinese databases—including China National Knowledge Infrastructure (CNKI), the Wanfang Data Knowledge Service Platform (WANFANG DATA), and Chinese VIP Data Platform—was implemented using a search time limit from 2003, the landmark event of SARS epidemics, until December 2020. This phase was carried out with the bibliometric software of CiteSpace V5.5 to extract frequently occurring titles to investigate the hot points on vulnerability and capability in disaster settings. Furthermore, as defined by the United Nations International Strategy for Disaster Reduction (UNISDR), the conceptual vulnerability is commonly impacted by material, social, economic, and environmental factors, which have been improved and applied in disaster assessment by a series of researchers. For example, Schoen et al. [44] presented a scorecard to assess and monitor domains of US health system performance and confirmed the significance of ‘societal texture’ for practical vulnerability assessment. Zhu and Li [38] expanded the division of economic, human, and political elements into the V-type integrated system. Jahmehr et al. [27] designed a conceptual framework and evaluated regional health care performance in the overall community. Aria et al. [45] highlighted the necessity of developing a vulnerability-centered framework based on social cohesion and integration. Drawing upon the studies presented above, we summarized that resilience in disaster context is a complex notion formed by multiple constituents and assessment angles, but it is generally considered that the level of regional public health risk (denoted herein by the “risk index”) is supposed to be affected by “vulnerability” and “disaster-coping capability” combined. Given that vulnerability and capability interact in the geographical space, the correlation between them usually reflects the status quo of the resilience level in public health disasters. On this inductive basis, accordingly, we constructed and proposed an analysis framework (Fig. 2) that aims to identify key potential determinants and assess urban resilience.

1 The V-typed analytical strategy is commonly applied to issue extraction and acquisition using literature mining and survey activities, as it is believed to be conducive to the integration of theory and practice. For the application, see Liu and Huang [46].
3.2. Criteria weight by Rough AHP method

The Rough AHP method is one of the extensively used tools in multi-index evaluation [47,48]. However, a rough number cannot effectively deal with group decisions in relation to multiple criteria. Therefore, we proposed herein the Rough AHP by combining Rough Set with conventional AHP. Rough Set is a mathematical tool particularly capable of dealing with subjective concepts. The procedures of this method are as follows:

First, field surveys were conducted to obtain a group decision matrix based on the hierarchical structure of assessment criteria. An expert team was invited to make pairwise comparisons on criteria prioritization to obtain the weights matrix. The $k^{th}$ expert pairwise comparison matrix $D_k$ can be expressed as Eq. (1), where $r_{ij}^k$ is the $k^{th}$ expert’s judgment value for the $i^{th}$ criterion importance compared with the $j^{th}$ criterion.

After the consistency test, the group decision matrix $D$ can be built following the Eq. (1), where $r_{ij} = (r_{ij}^1, r_{ij}^2, ..., r_{ij}^m)$. Then, we can obtain the group decision matrix by combining the above pairwise matrix.

$$D = \begin{bmatrix}
1 & r_{12}^k & \cdots & r_{1m}^k \\
1 & 1 & \cdots & \cdots \\
\vdots & \vdots & \ddots & \vdots \\
r_{m1}^k & r_{m2}^k & \cdots & 1
\end{bmatrix}$$

Second, we transformed the element $r_{ij}$ in group decision matrix $D$ into rough number form to obtain rough group decision-making matrix $R$. Furthermore, a rough number could be obtained in the $k^{th}$ pairwise comparison matrix, as shown in Eq. (2).

$$R N(r_{ij}) = [\min(r_{ij}^k), \max(r_{ij}^k)]$$ (2)

Furthermore, rough sequence $RN (r_{ij})$ and rough decision matrix $R$ could be obtained as shown in Eq. (3) and Eq. (4), respectively.

$$RN(r_{ij}) = \left\{ \begin{array}{c}
[r_{ij1}^L, r_{ij1}^U]
\{r_{ij2}^L, r_{ij2}^U\} \\
\vdots
\{r_{ijm}^L, r_{ijm}^U\}
\end{array} \right\}$$ (3)

$$R = \begin{bmatrix}
[1,1] & [r_{121}^L, r_{121}^U] & \cdots & [r_{1m1}^L, r_{1m1}^U] \\
[r_{121}^L, r_{121}^U] & [1,1] & \cdots & [r_{1m2}^L, r_{1m2}^U] \\
\vdots & \vdots & \ddots & \vdots \\
[r_{1m1}^L, r_{1m1}^U] & [r_{1m2}^L, r_{1m2}^U] & \cdots & [1,1]
\end{bmatrix}$$ (4)

Third, the rough weight $W_i$ of each criterion in different hierarchies could be calculated using Eq. (5). Each criterion’s overall weight was obtained using the Multiplication Synthesis Method (MSM) from the top level to the bottom level.

$$W_i = \prod_{i=1}^{m} r_{ij}^L m \prod_{i=1}^{m} r_{ij}^U, i = 1, 2, \cdots, m$$ (5)

However, the weights calculated above are formed with rough numbers containing the minimum and maximum values, which could cause deviations in assessment. Considering the Hurwicz principle [49], the optimistic index $a (0 \leq a \leq 1)$ was further introduced, as reflected risk propensities from expert interviewed, to transform the weights into crisp value shown in Eq. (6). Specifically, if experts are optimistic, it can set up a with a bigger value ($a > 0.5$). If they are pessimistic, a smaller value ($a < 0.5$) can be set. If they remain neutral, in other words, neither optimistic nor very pessimistic, the value of $a$ could be set as 0.5.

$$aLim(Weight) + (1-a)Lim(Weight), \text{ where } 0 \leq a \leq 1$$ (6)

Overall, based on the evaluation hierarchical structure, established by decomposing decision objectives into factors [50], criteria weights can be determined using the Rough AHP approach. Compared with conventional AHP, the preferences of individuals can be aggregated into group series using Rough AHP. By combing the objective and subjective information, we can provide roughly accurate recognition for the assessment guidance and correlated indicators.

3.3. Data processing and calculation

By the vulnerability-capability framework, the disaster response inevitably affects local emergency function and resilience. To carry out the urban resilience assessment, the critical data is of great significance to judge and implement measuring. Based on the urban cases in Jiangsu province, we conducted the data processing and made the regional resilience score calculation as follows:

Step 1: Taking into account data availability and provincial characteristics in practice, a hierarchy structure for the vulnerability and emergency capability assessment was developed using the selected assessment factors (see Table 1).

Step 2: The criteria weights were further determined using Rough AHP as constructed above. By design, we interviewed the advisory team, including six public health professionals, five local emergency management officials, 13 community residents, and four disaster prevention experts. The criteria weights were then calculated by the Rough AHP (see details in Section 3.2).

Step 3: We calculated vulnerability scores and capability scores among selected provinces. Data were collected from both China’s national and local census from 2003 to 2020 according to the criteria determined in Step 1.

Following the data processing procedures above, each criterion was then normalized to obtain a uniform dimension. Criteria positively related to vulnerability and capability were transformed by Eq. (7),
Although the one negatively related were transformed by Eq. (8).

$$D_1 = \frac{X_i - X_{i-min}}{X_{i-max} - X_{i-min}}$$  

$$D_2 = \frac{X_{i-max} - X_i}{X_{i-max} - X_{i-min}}$$  

Besides, vulnerability and capability scores (SV/EC) on each sampled region can be calculated using Eq. (9), where $w_j$ is the overall weight of criterion and $M_{ij}$ is the standardized value of criterion $j$ in selected province $i$. The regional resilience index ($R_i$) could be obtained with the calculated scores further by Eq. (10).

$$SV_{ij}/EC_i = \sum_{j=1}^{m} w_j M_{ij}$$  

$$R_i = EC_i/ SV_i$$

Also, the sensitivity analysis is undertaken to explore the changes of SV/EC and criteria weights under different optimistic index $a$ (see instruction in Eq. (6)), with corresponding implications proposed.

### 4. Results and discussion

According to the Rough AHP method and procedure for weight set up described in Section 3, we carried out a series of work on assessing urban resilience in a public health disaster context, including the establishment of assessing factors under the V-C framework, indicator weights of criteria, resilience score calculation, and robustness analysis. Here we take cities in Jiangsu province as the research target to disclose the results.

### 4.1. Assessment factors

Resilience is a multidimensional concept and construct which cannot be captured by a single variable. As highlighted in the literature review above, several factors contribute to regional resilience under the framework of vulnerability-capability, incorporating aspects of health resources, staff allocation, and type/density of infrastructure. In practice, there have been disputes over the assessment of resilience, such as subjective and vague judgments, making it difficult to evaluate accurately. Thus, an approach that can capture subjective judgments to reach a consensus is vital. Based on the analysis of the regional public health system and emergency response status, the vulnerability factors herein are classified into four aspects: facility resources, processing conditions, economic support, and social monitoring in line with the principles of reliability. Concerning the attributes of other indicators in public health performance, the capability herein is divided into public service, environmental regulation, financial guarantee, and risk prevention. On this basis, a semi-structured questionnaire with the Likert 5 grading was distributed to 15 professors and academic professionals majoring in disaster management and urban governance to acquire their perceived attitudes toward the chosen assessing indicators. All 15 questionnaires were eventually collected. We take the Score 3.75 (from the quartile) as the critical value between “general” and “important” and make the Standard Deviation (SD>1) as the criteria for indicator screening. Indicators that exceed this threshold value would be eliminated from the alternatives. Then we used the Cronbach’s Alpha and Split-half statistical method to make the reliability test. The final results showed that the overall Cronbach’s Alpha is 0.941 and the Split-half coefficient is 0.837, indicating that the questionnaire for the indicator screening fulfills the requirements of reliability according to the judging standard by Bland [50].

### Table 1
Assessment of indicators for urban resilience in the vulnerability-capability framework.

| Target layer | Main Factor | Indicators | Mean | SD |
|--------------|-------------|------------|------|----|
| Urban Vulnerability (V$_1$) | Vulnerability of Facility Resources (V$_{11}$) | 01. regional health/clinic technical staffs (V$_{111}$) | 4.3126 | 0.8736 |
| | | 02. hospital beds per 10,000 pop (V$_{112}$) | 4.3425 | 0.7984 |
| | | 03. ratio of psychological counselors/tutors per million population (V$_{113}$) | 4.0759 | 0.9702 |
| | | 04. reserve ratio of protective medical equipment per 10,000 pop (V$_{114}$) | 4.0283 | 0.6834 |
| | | 05. ICU beds per million population (V$_{115}$) | 4.9311 | 0.7328 |
| | Processing Condition (V$_{12}$) | 01. average daily yield of clinic wastes (V$_{121}$) | 4.2901 | 0.5366 |
| | | 02. average monthly yield of medical wastes discharged (V$_{122}$) | 4.3215 | 0.7652 |
| | | 03. health-related emergency plan annually (V$_{123}$) | 3.9123 | 0.9127 |
| | | 04. disinfection and purification annually (V$_{124}$) | 3.9724 | 0.9022 |
| | | 05. proportion of labor remuneration in regional GDP, per capita (V$_{125}$) | 4.5142 | 0.5432 |
| | Economy Support (V$_{13}$) | 02. proportion of local fiscal revenue in GDP (%) (V$_{131}$) | 3.9321 | 0.8543 |
| | | 03. disposable income per capita (V$_{132}$) | 4.2073 | 0.6938 |
| | | 04. balance of savings deposits per capita (V$_{133}$) | 4.3212 | 0.5961 |
| | | 05. electric power supply per capita (V$_{134}$) | 4.0245 | 0.6344 |
| | Vulnerability of Social Monitoring (V$_{14}$) | 01. registered urban unemployment rate (V$_{141}$) | 4.3721 | 0.6227 |
| | | 02. urban-rural consumption ratio (V$_{142}$) | 4.3559 | 0.6851 |
| | | 03. coverage of medical social security (V$_{143}$) | 4.3172 | 0.7336 |
| | | 04. urban registered unemployment ratio (V$_{144}$) | 4.2891 | 0.6671 |
| | | 05. proportion of medical & health personnel per 1000 pop (V$_{145}$) | 3.8552 | 0.8421 |
| Emergency Capability (C$_1$) | Capability of Public Service (C$_{11}$) | 01. nursing/medical institutions per 1,000 pop (C$_{111}$) | 4.4642 | 0.6745 |
| | | 02. volume of urban transport line (C$_{112}$) | 3.9351 | 0.7441 |
| | | 03. mileage of public transport per 1,000 pop (C$_{113}$) | 4.1362 | 0.7602 |
| | | 04. medical and health service centers (C$_{114}$) | 4.0344 | 0.7931 |
| | | 05. post & telecommunications business volume per capita (C$_{115}$) | 5.3512 | 0.6874 |
| | Environmental Regulation (C$_{12}$) | 01. reclamation ratio of medical solid waste per 10,000 pop (C$_{121}$) | 4.8341 | 0.5356 |
| | | 02. processing ratio of medical waste discharged (C$_{122}$) | 4.5852 | 0.5915 |
| | | 03. green coverage ratio of built-up urban regions (C$_{123}$) | 4.3659 | 0.7374 |
| | | 04. harmless water processing and sewage treatment plant (C$_{124}$) | 4.3412 | 0.6983 |
| | | 05. coverage of environmental monitoring station (C$_{125}$) | 4.3681 | 0.7785 |
| | Capability of Financial Guarantee (C$_{13}$) | 01. proportion of public health budget in regional GDP per capita (C$_{131}$) | 4.3146 | 0.8623 |
| | | 02. proportion of public health expenditure in government health expenditure (C$_{132}$) | 4.0243 | 0.9452 |
| | | 03. commercial insurance in social health expenditure per capita (C$_{133}$) | 3.8722 | 0.8653 |
| | | 04. proportion of total health expenditure in regional GDP (C$_{134}$) | 4.0192 | 0.7731 |
| | | 05. coverage ratio of town basic endowment insurance (C$_{135}$) | 3.8429 | 0.8137 |
| | Capability of Risk Prevention (C$_{14}$) | 01. proportion of illiterate population (C$_{141}$) | 4.1702 | 0.6673 |
| | | 02. proportion of illiterate population (C$_{142}$) | 4.1702 | 0.6673 |
| | | 03. diagnosis and treatment in hospitals and Community Health Service Center/Station per 10,000 pop (C$_{143}$) | 4.1436 | 0.8317 |
After completing the work above, a hierarchical assessment system for public health disaster response is established (Table 1). The corresponding data from 2015 to 2019 are acquired from statistical yearbooks of China’s eastern province of Jiangsu, governmental bulletins on regional economic and social development, and related public reports. For the missing values, we replaced them with the adjacent mean value with the rule of Least Square Criterion, as raised by Honda et al. [51]. Besides, we suggest that each factor’s weight can be determined by integrating multiple stakeholders’ preferences. Therefore, the data applied in this research include not only census data but also the subjective judgment of multiple experts who were invited to participate in the scoring process.

4.2. Criteria weights and score calculation

As stated in Section 3, an expert team majoring in disaster management and public health were invited to make pairwise comparisons on criteria prioritization to obtain the weights matrix. According to the specific survey team, we set the α value as 0.5 and obtained each response of interviewers through a comparison matrix (see details of Eq. (1)). Using Rough AHP, we integrated the preferences of all the interviewers by the set standard and eventually determined the criteria weights. The top indicators contributing to SV/EC were identified in accordance with their weights, as shown in Table 2.

As mentioned above, the method of Rough AHP herein tends to promote consensus in resilience assessment by integrating both objective and subjective merits. Values of selected indicators, as shown in Table 1, were obtained from regional census data in Jiangsu province. SV/EC and the resilience value of each sampled city can be calculated by Eq. (8) and Eq. (9) and the results are shown in Table 3.

Also, Fig. 3 displays regional public health resilience indices as a hierarchical map, revealing the discrepancy of 13 cities (prefecture level) in selected Jiangsu province. As the figure annotation shows, the urban resilience was divided into four classes (high, medium, average, and low), which was performed using the following approach: Based on the value of Mean (M) and Standard Deviation (SD), we used the SD classification method to analyze the average value of urban resilience R and made the equivalent ratio of SD 1: 1 as the criteria for spacing interval [52]. Specifically, by the judgment rules of $R < \text{M-SD}$, $\text{M-SD} \leq R < \text{M}$, $M \leq R < M + \text{SD}$ and $R \geq M + \text{SD}$, the resilience level (r) was divided from the low to the high level, namely low class (0.4736), average class (0.5791-0.6218), and high class (0.6218-0.7306).

4.3. Robustness analysis and discussion

As stated in Section 3, the weights and calculated resilience value of each city (prefecture level) are highly dependent on the value of optimistic index $\alpha$, which is set subjectively by decision makers. Thus, robustness analysis here is required to test how the criteria weights and SV/EC varies if the optimistic index is changed. To achieve the goal, we changed the value of $\alpha$ with 10 percent increment, and observed the weights and SV/EC accordingly. Table 4 shows the testing results. The results shown in Table 4 indicate that the cities of Suzian, Huai’an, and Lianyungang (prefecture level) are relatively vulnerable to public health disasters regardless of how the coefficient $\alpha$ changes. These cities are also located in the relatively under-developed region in east China, which ought to receive more attention for disaster mitigation and preparedness. In contrast, the city of Suzhou and Nanjing have more advantages, demonstrated by the statistical results, in coping with public health emergencies. The reason may be that the two cities are located in the most economically and socially developed regions in mainland China, which possess more substantial public health resources and excellent anti-disaster infrastructure as well as critical facilities. Moreover, the results imply that the development of the economic level has an impact on the practical public health emergency system. More precisely, developed regions usually obtain more adequate resources and priority for disaster mitigation, which to some extent further enhance their resilience capability in coping with disasters.

Besides, as shown in Table 4, the selected top 10 criteria of indicators preserve their top positions regardless of how $\alpha$ changes, indicating the most important factors contributing to urban disaster resilience. The sub-factors can be divided into four categories, namely regional vulnerability (VF, $V_{134}$, $V_{135}$), vulnerability of supporting resources ($V_{122}$, $V_{124}$), supply capacity of medical facilities ($C_{111}$, $C_{114}$, $C_{121}$, $C_{125}$) and regional expenditure ($C_{132}$, $C_{134}$). It is noted that public health disaster response is linked with economic power, regional finances, and supporting resources, which closely contribute to the effective handling of hazards. The power of economic level in 13 cities of Jiangsu province (geographical distribution of north, midst, and south regions) is reflected in managing the COVID-19 pandemic. Suzhou and Nanjing, the most developed metropolitan cities in the surveyed region, are earlier to recover from the pandemic and achieve better economic growth (Xinhua News Agency, 2020). For example, Nanjing, the provincial capital of Jiangsu, was hit by COVID-19 in July 2021 due to the loopholes of the Lukou international airport. However, relying on strong urban response capacity and resilience construction resources, the city achieved the target of zero infected cases and effective control barely after 24 days, and the urban society quickly returned to normal (Shangguan Net, 2021). More precisely, the relatively developed urban region in Jiangsu handled the sudden health disaster with better performance, both in emergency response efficiency and related post-disaster recovery. As indicated in the above sections, urban resilience in public health disasters is affected by elements of vulnerability and capacity combined. Since 2019, when the COVID-19 pandemic broke out in China, cities in

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Table 2

| Indicator                                                                 | Weight | Rank |
|---------------------------------------------------------------------------|--------|------|
| Average monthly yield of medical waste discharged (V_{122})              | 0.0667 | 8    |
| Balance of savings deposits per capita (V_{134})                         | 0.0813 | 4    |
| Electric power supply per capita (V_{123})                               | 0.0769 | 7    |
| Proportion of medical & health personnel per 1000 (V_{142})              | 0.0927 | 3    |
| Nursing/medical institutions per 1,000 (C_{111})                        | 0.0491 | 10   |
| Medical & health service center (C_{114})                               | 0.0782 | 5    |
| Reclamation rate of medical solid waste per 10 000(C_{217})              | 0.0662 | 6    |
| Coverage of environmental monitoring stations (C_{227})                  | 0.0538 | 9    |
| Proportion of public health expenditure in government health expenditure (C_{332}) | 0.1076 | 2    |
| Proportion of total health expenditure in regional GDP (C_{334})          | 0.1103 | 1    |

Table 3

| City (prefecture level) | Resilience | Rank |
|-------------------------|------------|------|
| Nanjing                 | 0.7126     | 1    |
| Suzhou                  | 0.6583     | 2    |
| Wuxi                    | 0.6427     | 3    |
| Changzhou               | 0.6096     | 4    |
| Zhenjiang               | 0.5933     | 5    |
| Nantong                 | 0.5825     | 6    |
| Yangzhou                | 0.5738     | 7    |
| Taizhou                 | 0.5423     | 8    |
| Xuzhou                  | 0.5411     | 9    |
| Huai’nan                | 0.4926     | 10   |
| Suqian                  | 0.4837     | 11   |
| Yangcheng              | 0.4729     | 12   |
| Lianyungang             | 0.4602     | 13   |

2 “No new cases of infection for 6 consecutive days. The city of Nanjing quickly switch to low risk!” Shangguan Net. https://ww.qq.com/partner/vivoscreen/20210819A06MSX/20210819A06MSX007sNews=1 [2021-08-19].
Jiangsu have vigorously invested in and constructed the infrastructure and facilities for disaster reduction, such as community resilience and disaster mitigation program, to increase resilience capacity significantly. In contrast, regions at the grass-roots level, are still inadequate in providing necessary public health resources and are vulnerable to hazards. That might be the reason why the vulnerability index remains high in the northern parts of Jiangsu province.

5. Conclusion

For urban resilience assessment in public health disasters, a Rough AHP method on the basis of vulnerability-capability framework was proposed in the study and applied to the 13 cities (prefecture level) in Jiangsu province, China. Due to the uncertainty and coupling effects among various urban hazards, it is not rational to assess resilience in actual disaster response without considering the individual perceptions and the completeness of indicators. Therefore, we determined the assessment criteria weights and calculated the corresponding resilience index using the Rough AHP approach. The results showed the spatial discrepancy of disaster-coping resilience in the sampled cities. Moreover, critical factors contributing to local vulnerability were derived by the robustness analysis to facilitate informed decisions on the reduction of a public health disaster, especially after the COVID-19 pandemics. What needs to be stressed is that the urban disaster management system in public health is a complex dynamic mechanism. It is inappropriate to rely on any single element to reduce the disastrous risk. Considering methodology, this resilience assessment by the vulnerability-capability framework provides relevant knowledge-based information for scholars and practitioners in handling public health disasters. The validation process contributes to future exploration for urban resilience research.

The study shows the advantages of the proposed Rough AHP method and its applicability in urban resilience assessment. However, there are also limitations due to uncertainties. First, the factors contributing to vulnerability and capability are assumed to be independent based on Rough AHP, without considering the inter-dependency of multiple influential factors. Thus, it is evident that an additionally refined model or framework is required to better understand the correlations among factors methodologically. The Analytic Network Process (ANP), a generalization of AHP with personal feedback to adjust index weights, may be a solution in the study. Second, some panel data were obtained from published statistical yearbooks (2015-2019) in Jiangsu, and might not have considered the endogenous factor in regional spatial discrepancy. Future research will be devoted to improving the data collection pathway and coverage of different administrative levels by integrating the propitiated statistical approach and system dynamic method.

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**Declaration of Competing Interest**

The authors declare no conflict of interest.

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**Appendix**

The raw data of constructed indicators in 13 cities of Jiangsu province.
Table A1
The raw data of constructed indicators in 13 cities of Jiangsu province.

| City         | 2015   | 2016   | 2017   | 2018   | 2019   |
|--------------|--------|--------|--------|--------|--------|
| Nanjing      | 122404 | 125255 | 132652 | 135183 | 133978 |
| Wuxi         | 40726  | 42493  | 43838  | 42048  | 45822  |
| Xuzhou       | 25950  | 24350  | 26199  | 26708  | 31805  |
| Changzhou    | 25408  | 29537  | 30825  | 31591  | 36090  |
| Suzhou       | 72698  | 74925  | 78279  | 81716  | 78082  |
| Nantong      | 22886  | 28150  | 29277  | 29703  | 29768  |
| Lianyungang  | 10719  | 12984  | 14298  | 12926  | 12228  |
| Huai’an      | 15881  | 16107  | 17831  | 17835  | 22218  |
| Yancheng     | 7817   | 10862  | 10953  | 11300  | 11672  |
| Yangzhou     | 17878  | 19051  | 19376  | 18999  | 20563  |
| Zhenjiang    | 16929  | 17297  | 17710  | 16411  | 16327  |
| Taizhou      | 9258   | 9343   | 10238  | 9987   | 10669  |
| Suqian       | 7632   | 7358   | 8064   | 8297   | 8486   |

Table A1 (continued)

| City         | 2015   | 2016   | 2017   | 2018   | 2019   |
|--------------|--------|--------|--------|--------|--------|
| Nanjing      | 15     | 15.1   | 15.3   | 15.6   | 15.5   |
| Wuxi         | 14.8   | 14.9   | 14.9   | 14.9   | 14.9   |
| Xuzhou       | 16.2   | 15.3   | 15.7   | 14.7   | 14.3   |
| Changzhou    | 13.2   | 13.9   | 14.5   | 14.9   | 12.2   |
| Suzhou       | 15.2   | 15.1   | 14.7   | 13.9   | 13     |
| Nantong      | 16.8   | 17     | 18.5   | 19     | 19     |
| Lianyungang  | 14.2   | 14.4   | 14.7   | 14.1   | 14.4   |
| Huai’an      | 13.8   | 13.8   | 14     | 14.6   | 14.2   |
| Yancheng     | 12     | 12.4   | 12.8   | 13.7   | 14.2   |
| Yangzhou     | 18     | 18.4   | 18.6   | 18.8   | 18     |
| Zhenjiang    | 18.7   | 18.9   | 19     | 19.1   | 19.1   |
| Taizhou      | 9.5    | 10     | 10.7   | 14.5   | 14.9   |
| Suqian       | 13.8   | 15.1   | 15.3   | 15.5   | 15.5   |

Table A2
The raw data of tonnage of constructed indicators in 13 cities of Jiangsu province.

| City         | 2015   | 2016   | 2017   | 2018   | 2019   |
|--------------|--------|--------|--------|--------|--------|
| Nanjing      | 11     | 11.2   | 10.6   | 12.1   | 12.1   |
| Wuxi         | 15.9   | 39.4   | 39.5   | 24.6   | 24.6   |
| Xuzhou       | 12.2   | 8.4    | 8.4    | 6.9    | 6.9    |
| Changzhou    | 17.4   | 22.5   | 22.5   | 14.4   | 17.5   |
| Suzhou       | 18.3   | 19.4   | 18.8   | 15.2   | 16.6   |
| Nantong      | 16.3   | 20.8   | 20.9   | 20.8   | 20.7   |
| Lianyungang  | 13.1   | 9.2    | 10.1   | 6.7    | 6.7    |
| Huai’an      | 30     | 13.1   | 14.1   | 16     | 15.5   |
| Yancheng     | 20.9   | 14.2   | 14.6   | 6.8    | 4.6    |
| Yangzhou     | 23.9   | 17.2   | 17.4   | 16.2   | 16.2   |
| Zhenjiang    | 18.2   | 14.2   | 14.5   | 10.1   | 10.4   |
| Taizhou      | 23     | 16.6   | 16.4   | 16.4   | 15.2   |

Table A2 (continued)

| City         | 2015   | 2016   | 2017   | 2018   | 2019   |
|--------------|--------|--------|--------|--------|--------|
| Nanjing      | 261    | 239    | 213    | 285    | 311    |
| Wuxi         | 122    | 132    | 142    | 158    | 165    |
| Xuzhou       | 75     | 80     | 92     | 104    | 119    |
| Changzhou    | 62     | 76     | 84     | 81     | 111    |
| Suzhou       | 214    | 240    | 246    | 273    | 248    |
| Nantong      | 53     | 60     | 72     | 80     | 85     |
| Lianyungang  | 24     | 36     | 40     | 45     | 65     |
| Huai’an      | 38     | 43     | 55     | 59     | 68     |
| Yancheng     | 32     | 36     | 41     | 47     | 45     |
| Yangzhou     | 49     | 53     | 66     | 56     | 68     |
| Zhenjiang    | 32     | 36     | 41     | 47     | 45     |
| Taizhou      | 28     | 29     | 31     | 37     | 43     |
| Suqian       | 25     | 27     | 28     | 29     | 35     |

(continued on next page)
### Table A1 (continued)

| V₁₃₂ (%) | 2015 | 2016 | 2017 | 2018 | 2019 |
|----------|------|------|------|------|------|
| Nanjing  | 10.2 | 10.3 | 10.7 | 10.9 | 11.2 |
| Wuxi     | 8.6  | 8.5  | 8.7  | 8.7  | 8.7  |
| Xuzhou   | 6.9  | 6.4  | 6.5  | 6.6  | 6.6  |
| Changzhou| 7.7  | 7.7  | 7.8  | 7.9  | 7.9  |
| Suzhou   | 10.9 | 10.4 | 10.9 | 11.3 | 11.5 |
| Nantong  | 6.2  | 6.9  | 6.5  | 6.4  | 6.6  |
| Lianyungang| 7.4 | 7.2  | 7.1  | 6.5  | 7.7  |
| Hua’ian  | 6.8  | 6.8  | 6.6  | 6.6  | 6.7  |
| Yancheng | 6.6  | 6.6  | 6.5  | 5.6  | 5.7  |
| Yangzhou | 5.7  | 5.8  | 5.5  | 5.6  | 5.7  |
| Zhenjiang| 7.4  | 7.5  | 7.3  | 7.4  | 7.4  |
| Taizhou  | 7.3  | 7.1  | 7.2  | 7.2  | 7.3  |
| Suzian   | 6.6  | 6.6  | 6.7  | 6.8  | 6.8  |

| V₁₃₃ (%) | 2015 | 2016 | 2017 | 2018 | 2019 |
|----------|------|------|------|------|------|
| Nanjing  | 62068| 65139| 70687| 76144| 84097|
| Wuxi     | 41563| 44707| 47549| 51015| 54733|
| Xuzhou   | 47007| 51567| 55523| 57536| 67412|
| Changzhou| 28090| 29616| 31194| 32498| 34856|
| Suzhou   | 64281| 68179| 72166| 79623| 85188|
| Nantong  | 39481| 41067| 43570| 45640| 48041|
| Lianyungang| 21896| 23056| 26152| 27540| 28847|
| Hua’ian  | 28976| 30475| 31324| 32310| 34883|
| Yancheng | 36634| 39494| 42087| 42822| 57782|
| Yangzhou | 23338| 24236| 25273| 28609| 27508|
| Zhenjiang| 18373| 18985| 19449| 20368| 21080|
| Taizhou  | 22965| 24215| 26094| 27309| 29390|
| Suzian   | 25862| 26179| 28412| 30400| 31687|

| V₁₃₄ (%) | 2015 | 2016 | 2017 | 2018 | 2019 |
|----------|------|------|------|------|------|
| Nanjing  | 4167.19| 4590.17| 5088.2| 5604.66| 5832.46|
| Wuxi     | 1500.41| 1635.49| 1769.14| 1981.83| 2056.14|
| Xuzhou   | 1315.77| 1472.06| 1655.21| 1795.09| 1898.4|
| Changzhou| 1348.58| 1715.15| 1899.81| 2122.39| 2256.37|
| Suzhou   | 2133.71| 2371.12| 2558.5| 2804.95| 2955.9|
| Nantong  | 856.6 | 931.44| 1029.13| 1119.61| 1205.6|
| Lianyungang| 430.9 | 484.42| 544.44| 605.05| 653.85|
| Hua’ian  | 514.73| 576.7 | 739.14| 814.96| 857.32|
| Yancheng | 448.71| 657.31| 730.23| 426.34| 798.16|
| Yangzhou | 774.56| 849.08| 928.61| 1020.48| 1054.59|
| Zhenjiang| 517.79| 573.84| 638.23| 647.3| 668.12|
| Taizhou  | 448.03| 496.09| 556.91| 629.18| 638.13|
| Suzian   | 255.27| 268.86| 301.98| 332.34| 356.56|

| V₁₃₅ (kWh) | 2015 | 2016 | 2017 | 2018 | 2019 |
|------------|------|------|------|------|------|
| Nanjing    | 903.49| 1020.03| 1142.6| 1271.91| 1470.02|
| Wuxi       | 472.9 | 508.58| 536.44| 583.7| 638.23|
| Xuzhou     | 241.06| 270.88| 268.56| 274.75| 289.01|
| Changzhou  | 353.14| 410.09| 421.86| 457.43| 494.04|
| Suzhou     | 763.62| 829.55| 919.82| 1012.91| 1132.56|
| Nantong    | 242.62| 272.67| 263.54| 260.06| 273.6|
| Lianyungang| 153.86| 172.58| 144.91| 151.28| 166.48|
| Hua’ian    | 204.39| 232.89| 233.75| 172.92| 185.73|
| Yancheng   | 139.59| 224.42| 198.42| 178.17| 187.63|
| Yangzhou   | 203.94| 233.57| 253.63| 212.17| 224.72|
| Zhenjiang  | 146.97| 161.74| 154.48| 147.28| 157.33|
| Taizhou    | 141.88| 161.31| 174.41| 184.71| 187|
| Suzian     | 88 | 98.66| 101.24| 100.03| 107.71|

| V₁₄₁ (%) | 2015 | 2016 | 2017 | 2018 | 2019 |
|----------|------|------|------|------|------|
| Nanjing  | 1.88 | 1.8 | 1.78 | 1.81 | 1.82 |
| Wuxi     | 1.9 | 1.9 | 1.8 | 1.8 | 1.8 |
| Xuzhou   | 1.9 | 1.8 | 1.8 | 1.8 | 1.8 |
| Changzhou| 1.9 | 1.8 | 1.8 | 1.8 | 1.8 |
| Suzhou   | 1.9 | 1.8 | 1.8 | 1.8 | 1.8 |
| Nantong  | 1.9 | 1.8 | 2.0 | 1.78 | 1.78 |
| Lianyungang| 2.0 | 1.9 | 1.9 | 1.8 | 1.8 |
| Hua’ian  | 2.2 | 2.2 | 1.9 | 1.8 | 1.8 |
| Yancheng | 2.0 | 1.8 | 1.8 | 1.8 | 1.8 |
| Yangzhou | 2.0 | 1.9 | 1.8 | 1.8 | 1.8 |
| Zhenjiang| 1.9 | 1.8 | 1.8 | 1.8 | 1.8 |
| Taizhou  | 1.9 | 1.8 | 1.8 | 1.8 | 1.8 |
| Suzian   | 2.0 | 1.9 | 1.8 | 1.8 | 1.8 |

(continued on next page)
### Table A1 (continued)

| C_{112} (mileage) | 2015 | 2016 | 2017 | 2018 | 2019 |
|-------------------|------|------|------|------|------|
| Nanjing           | 109194 | 119883 | 129194 | 141103 | 152886 |
| Wuxi              | 128756 | 133515 | 149885 | 160076 | 174270 |
| Xuzhou            | 58308 | 62246 | 67701 | 75611 | 76915 |
| Changzhou         | 106329 | 114308 | 124889 | 140435 | 149277 |
| Suzhou            | 132311 | 139127 | 148146 | 162388 | 173765 |
| Nantong           | 78777 | 85712 | 94304 | 105903 | 115320 |
| Lianyungang       | 44757 | 48977 | 53626 | 58577 | 61332 |
| Hua’ian           | 51213 | 57032 | 63083 | 67909 | 73204 |
| Yancheng          | 53713 | 58993 | 64065 | 70216 | 75987 |
| Zhenjiang         | 104352 | 112225 | 122686 | 125962 | 126906 |
| Taizhou           | 79825 | 80779 | 89785 | 102058 | 109988 |
| Suzian            | 40322 | 44275 | 48797 | 53317 | 55906 |

| C_{114} (number) | 2015 | 2016 | 2017 | 2018 | 2019 |
|------------------|------|------|------|------|------|
| Nanjing          | 34213 | 40455 | 44009 | 48104 | 59308 |
| Wuxi             | 33503 | 39461 | 42577 | 46453 | 55113 |
| Xuzhou           | 17042 | 20425 | 23248 | 24535 | 27398 |
| Changzhou        | 29901 | 35379 | 38435 | 41879 | 54000 |
| Suzhou           | 36533 | 42897 | 46595 | 50603 | 63481 |
| Nantong          | 23147 | 27584 | 30084 | 33011 | 42398 |
| Lianyungang      | 16103 | 19418 | 21230 | 23932 | 35379 |
| Hua’ian          | 17364 | 20864 | 22762 | 24934 | 29341 |
| Yancheng         | 18676 | 22419 | 24463 | 26740 | 40060 |
| Yangzhou         | 21992 | 26253 | 28633 | 31370 | 38924 |
| Zhenjiang        | 26327 | 31263 | 34064 | 37169 | 48325 |
| Taizhou          | 21734 | 25927 | 28259 | 30944 | 44384 |
| Suzian           | 14312 | 17242 | 18957 | 20756 | 29483 |

| C_{115} (km)     | 2015 | 2016 | 2017 | 2018 | 2019 |
|------------------|------|------|------|------|------|
| Nanjing          | 50557 | 55355 | 58947 | 60197 | 69148 |
| Wuxi             | 4341.45 | 4639.66 | 4876.43 | 5005.54 | 5111.59 |
| Xuzhou           | 2377.44 | 2780.6 | 3090.21 | 3394.45 | 3604.84 |
| Changzhou        | 2934.19 | 3193.77 | 3266.85 | 3532.34 | 3841.9 |
| Suzhou           | 6271.73 | 7538.04 | 7913.85 | 8166.46 | 9148.5 |
| Nantong          | 4602.87 | 5115.5 | 5544.89 | 5816.35 | 6287.26 |
| Lianyungang      | 924.03 | 1048.27 | 1168.71 | 1297.49 | 1420.02 |
| Hua’ian          | 1044.52 | 1183.92 | 1360.51 | 1483.1 | 1605.25 |
| Yancheng         | 2062.39 | 2397.52 | 2682.46 | 2892.3 | 3171.33 |
| Yangzhou         | 2177.09 | 2376.68 | 2560.98 | 2664.64 | 2860.65 |
| Zhenjiang        | 1569.40 | 1969.11 | 1982.67 | 2161.07 | 2307.01 |
| Taizhou          | 1984.8 | 4441.7 | 2474.71 | 2635.6 | 2876.63 |
| Suzian           | 813.2 | 1819.81 | 1086.33 | 1299.5 | 1344.78 |

| C_{121} (%)      | 2015 | 2016 | 2017 | 2018 | 2019 |
|------------------|------|------|------|------|------|
| Nanjing          | 2.16 | 2.23 | 2.53 | 2.81 | 3.16 |
| Wuxi             | 0.97 | 1.04 | 1.14 | 1.24 | 1.33 |
| Xuzhou           | 0.87 | 0.94 | 1.05 | 1.08 | 1.33 |
| Changzhou        | 0.85 | 1.02 | 1.06 | 1.12 | 1.2 |
| Suzhou           | 1.27 | 1.33 | 1.39 | 1.61 | 1.78 |
| Nantong          | 0.71 | 0.76 | 0.78 | 0.84 | 0.8 |
| Lianyungang      | 0.5 | 0.51 | 0.61 | 0.62 | 0.66 |
| Hua’ian          | 0.68 | 0.69 | 0.83 | 0.86 | 0.9 |
| Yancheng         | 0.41 | 0.63 | 0.67 | 0.69 | 0.71 |
| Yangzhou         | 0.58 | 0.61 | 0.64 | 0.68 | 0.69 |
| Zhenjiang        | 0.39 | 0.4 | 0.41 | 0.41 | 0.41 |
| Taizhou          | 0.41 | 0.42 | 0.44 | 0.47 | 0.51 |
| Suzian           | 0.26 | 0.3 | 0.33 | 0.36 | 0.41 |

(continued on next page)
Table A1 (continued)

| City            | 2015 | 2016 | 2017 | 2018 | 2019 |
|-----------------|------|------|------|------|------|
| Nanjing         | 313  | 374  | 401  | 428  | 469  |
| Wuxi            | 155  | 178  | 167  | 194  | 203  |
| Xuzhou          | 58   | 105  | 113  | 130  | 155  |
| Changzhou       | 185  | 187  | 209  | 234  | 240  |
| Suzhou          | 214  | 241  | 284  | 320  | 330  |
| Nantong         | 78   | 43   | 104  | 105  | 122  |
| Lianyungang     | 66   | 68   | 79   | 86   | 93   |
| Huaian          | 41   | 29   | 31   | 40   | 28   |
| Yancheng        | 43   | 70   | 85   | 94   | 93   |
| Yangzhou        | 55   | 58   | 101  | 109  | 118  |
| Zhenjiang       | 40   | 47   | 38   | 75   | 64   |
| Taihu           | 43   | 57   | 67   | 78   | 77   |
| Suqian          | 35   | 43   | 47   | 49   | 54   |

| City          | 2015 | 2016 | 2017 | 2018 | 2019 |
|---------------|------|------|------|------|------|
| Nanjing       | 5.89 | 5.91 | 5.96 | 5.99 | 6.02 |
| Wuxi          | 5.8  | 5.82 | 5.84 | 5.88 | 5.97 |
| Xuzhou        | 5.89 | 5.91 | 5.96 | 6.03 | 6.14 |
| Changzhou     | 5.68 | 5.73 | 5.76 | 5.77 | 5.84 |
| Suzhou        | 5.94 | 6.11 | 6.17 | 6.22 | 6.22 |
| Nantong       | 5.68 | 5.76 | 5.82 | 5.84 | 5.89 |
| Lianyungang   | 5.24 | 5.28 | 5.32 | 5.38 | 5.49 |
| Huaian        | 4.71 | 4.79 | 5.04 | 5.11 | 5.23 |
| Yancheng      | 4.94 | 5.02 | 5.08 | 5.21 | 5.26 |
| Yangzhou      | 4.61 | 4.62 | 4.69 | 4.74 | 4.78 |
| Zhenjiang     | 4.71 | 4.73 | 4.78 | 4.81 | 4.89 |
| Taihu         | 4.57 | 4.63 | 4.66 | 4.72 | 4.76 |
| Suqian        | 4.57 | 4.63 | 4.66 | 4.72 | 4.76 |

Note: Abbreviations of indicators for $V_{ip}$ and $C_{ip}$ are shown in Table 1 of the article.

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