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Time and space model of urban pollution migration: Economy-energy-environment nexus network

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HIGHLIGHTS

- 3E Networks are constructed to untangling the causal web linking urbanization and human health.
- Appearance of a cancer village is result of spatial-temporal distribution of human-land interaction.
- Incidences are not just because of surrounding cities also due to far-away city through network.
- Mitigation of the adverse effects of urbanization need to meet the people's health care demands.

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ABSTRACT

In recent years, news of "cancer villages" in the Huaihe River Basin filled front and back pages of newspapers and generated elevated concern among readers. This study aims to understand the relationship between the "cancer villages" and the "large cities" around them. A gravity model is constructed to analyze the correlation between "big cities" and "cancer villages" in terms of indices involving economic connections and pollution frequency. Direct and indirect environmental relationships between large cities and "cancer villages" are analyzed using ecological network analysis, in particular the utility analysis method. Results of the pollution-utility analysis showed that cities distant from "cancer villages" can also affect the county through indirect connections. Based on the pollution utility relationship, we found that "cancer villages" both affect and are affected by cities through indirect feedback relationships. It can be inferred that "cancer villages" have a high incidence of malignant disease not only because of the pollution from its surrounding cities but also because of the influence of far-away cities through a network of interactions. In this way, the pollution of "cancer villages" may be heightened with harmful consequences to population health. Considering these indirect connections, not all of the "cancer villages" are able to reduce their pollution by transferring it to another city or county because it can return through indirect pathways. The best approach would be to lower the pollution generation in the first place in order to prevent its impacts, as well as to at least partially mitigate them through more effective medical care.

1. Introduction

With reports about "cancer villages" in the Huaihe River Basin by several media outlets since 2004 (Google Map, China's Cancer Villages), the phenomenon has drawn general attention to the frequent occurrences of tumors in the area. In accordance with the tumor death review survey published in the 1970s (Editorial Committee of Tumor Death Maps, 1979), there is a low frequency of tumor mortality upstream of Huaihe River, *e.g.*, gastrointestinal tumors and lung cancer mortality rates are below the national average (the exception is esophageal cancer). However, reported cancer villages now total several dozen along Huaihe River based on media reports since 2004 [1]. Shayinghe River, the largest tributary of Huaihe River, flows through Shenqiu County, where small chemical enterprises and large state-owned chemical enterprises

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working on weaving and painting, leather, and paper production are located upstream [2,3]. The river is also subject to increasing sewage discharge pressure. From Xiangcheng and Shenqiu to Yingshan in Anhui, there have been no less than 10 cancer villages revealed by the media, and many more evidenced by social media such as micro-blogs.[1] For instance, a volunteer working on long-term environmental protection inspection and publicity discovered more than 20 cancer villages with 100 people suffering from cancer in Shenqiu [4]. Due to the fact that the Huaihe River Basin plays an important role in the economic and social development in China, and to the high incidence of cancer occurrence in this area, research is needed to understand and alleviate this phenomenon.

Published research points out that water pollution is closely related to the high incidence of cancer [5]. The distribution of cancer villages is in close relation to the rivers: nearly 60% of cancer villages are found within 3 km of the rivers, and nearly 81% of cancer villages are located within 5 km of the rivers [6]. Such finding suggests that the rivers are an important factor affecting cancer distribution. In addition, the "Atlas of water environment and gastrointestinal tumor mortality in the Huaihe River Basin", part of the achievement of the "Correlation assessment study of water pollution and tumor" by the "Eleventh Five-year Plan" National Science and Technology Support Project, was officially published in June, 2013. The atlas, for the first time, confirmed a direct relationship between water pollution and a high incidence of cancer. Regretfully, the existing research lacks an exploration of the relationship of environmental impact between the cities within the river area and adjacent counties, as well as whether cities exert environmental influence on adjacent counties (including on human health). Therefore, this study was conducted for the following purposes: (1) to analyze the influence between cancer villages and the adjacent cities, as well as the strength of influence, (2) to establish a gravity model of the relationship concerning regional characteristic factors (distance, population, economy, and pollution degree) between cancer villages and the adjacent cities; (3) to analyze the relationship between cancer villages and the adjacent rivers and to determine if the high incidence of cancer has a higher correlation with river pollution; (4) to conduct a network analysis of cancer villages in the Huaihe River Basin and large- and medium-sized cities, as well as to determine if there is an indirect link between cancer villages and the adjacent cities; and (5) to provide a reference and policy guidance for research on the formation of cancer villages and cities' pollution impact on cancer villages in the river area.

2. State of the art

2.1. Relationship between urban pollution and the regional environment

Research on urbanization and urban ecological environments began in China in the 1970s and has continued with a rapid progress [7]. The main focus involves urban environmental effects caused by urbanization, the coordinated urban development of society, economy, and environment, sustainable city development, ecological city, and healthy city development, among others [8].

Water resources and water environmental problems brought about by urbanization include absolute scarcity of water, relative scarcity of water, water pollution, and excess groundwater exploitation. Adopting advanced GIS (Geographic Information System) and RS (Remote Sensing) methods and using numerical simulation, a large number of long-term research projects have been performed on these topics. For example, Al-Kharabsheh and Ta'any [9] conducted locating and tracking research on urbanization and surface water quality. A bulletin on environmental conditions [10] indicated that surface water pollution is still serious in China due to urban industrial pollution. The water quality of the seven waters (Yangtze River, Yellow River, Zhujiang River, Songhuajiang River, Huaihe River, Haihe River, and Liaohe River) is basically the same as the year of 2007. The overall water quality in the Zhujiang and Yangtze rivers is good, while the Songhuajiang River remains lightly polluted. The Yellow River, Huaihe River, and Liaohe River remain moderately polluted, and the Huaihe River is seriously contaminated. Among the 26 lakes and reservoirs monitored for nutritional status, 46.2% are eutrophic. DeNooyer et al. [11] focused on the state of Illinois, combined existing digital spatial datasets with engineering basic principles to synthesize a geographic information systems (GIS) model of current and projected water demand for thermoelectric power plants. Nanduri and Saavedra-Antolinez [12] developed a CMDP model for the energy–water–climate change nexus.

Zhang [13] says that the expansion of cities has provided humans with favorable living and working environments but also caused considerable harm to the urban environment due to pollutant emissions from factories and daily life. Because of rainfall, the pollutants will spread, move, and then be deposited in new locations. Due to the fact that pollutants in the atmosphere are soluble in or carried by water, they can be transferred to the ground, underground, and even to remote areas, affecting the downwind or downstream areas. Industrial sewage also flows through sewers into rivers and lakes, contaminating surface water and even groundwater by means of the soil. Gao et al. [14] states that with the quickening pace of urbanization in China and the rapid development of industrialization, population growth, and gradual improvement of people's living standards, water consumption has dramatically increased, and industrial waste water and urban sewage emissions are rapidly increasing. Thus, the conflict between the shortage of water resources and economic and social development is becoming more intense. Wang et al. [15] showed evidence that the increasing amount of industrial pollution in rural areas directly results in the deterioration of rural water, soil, and air; the livelihood and health of the masses of rural farmers are seriously affected; and the rural areas pay a huge price for the rapid growth of Zhejiang province. Xu [16] indicates in his study of ecosystem health problems in Dianchi Basin that pollution control acts as the key to reach the functional standard of the river basin water environment. Briefly, the environmental carrying capacity of rivers has two connotations: quantity and space. Thus, aside from the control of emissions, the layout of the pollutant source is of great importance to successfully reach water environment quality standards.

Several scholars have conducted research into the relationship between urban pollution migration and regional ecological impact. Regarding the issue of the relocation of pollution-causing enterprises, a geographical analysis method is usually adopted, including the urban land use model by Burgess [17], the backwash effects and spread effects by Myrdal [18], and the polarization effects by Hirschman [19]. These traditional methods still play an important role in today's resource management and allocation. For example, Ahlfeldt [20] found the mono-centric model useful in certain conditions, and Arauzo-Carod et al. [21] concludes that the relationship between econometric methods and related location theories is relatively weak concerning the relocation of pollution-causing enterprises. In their estimation, an increasing number of scholars will study the relocation of pollution-causing enterprises after the appearance of a new data collection strategy and solution to the problem of data sources. Liu et al. [22] used an extended STIRPAT model to investigate the effects of human

[1] http://s.weibo.com/weibo/%25E7%2599%258C%25E7%2597%2587%25E6%259D%2591?topnav=1&wvr=6&b=1.

activity on energy consumption and three types of industrial pollutant emissions (exhaust gases, waste water and solid waste) at the national and regional levels and tested the environmental Kuznets curve (EKC) hypothesis based on a balanced provincial panel dataset in China over the period 1990–2012. The results show that because of the regional disparities in anthropogenic impact on the environment, formulating specific region-oriented energy saving and emission reduction strategies may provide a more practical and effective approach to achieving sustainable development in China. Xing et al. [23] determined the influence of backwash effects and spread effects in Changsha, Zhujiang River, and Xiangtan in China, while Forrer et al. [24] found that the key cities of China have exerted a backwash effect on the nearby rural counties and villages and a spread effect on other cities. Unfortunately, these geographical methods have not been widely applied to the study of sustainable development.

2.2. Spatial distribution of affected areas

Studies demonstrate that the distribution of cancer villages is not arbitrary in space [6,25]. It is, instead, closely correlated with geographical factors, such as distance from and direction to cities, with economy size, population, and environment pollution. Moreover, one characteristic of the high incidence of cancer near the Huaihe River is that gastrointestinal tumors are especially prevalent, not on both sides of the river but near first and second category tributaries, even smaller tributaries, and villages within 2.5 km of polluted tributaries.

Scientific studies about cancer villages, at present, mainly focus on two aspects: (1) the cause and (2) their temporal (The Third Death Review Survey Report, 2008; Report of Cancer Death in China, 2010; [26–28] and spatial distribution [29–31]. For instance, Wang et al. [26] researches cancer villages in Shaanxi Province and a geochemical element analysis of seven samples (water, flour, beans, potatoes, tomatoes, soil, and rocks) from the cancer village in Huaxian County, as well as trace element analysis of samples of hair. The preliminary conclusion of this work is that arsenic, lead, and cadmium pollution is the major cause of cancer in this village. Lin [27] points out that total coliform group and total bacteria in the groundwater of this village exceed standards by up to 100% and 41.2%, respectively; the nitrate nitrogen concentration also averages 15.2 mg/L. The conclusion is that drinking water contaminated with polluted groundwater is related to the high incidence of cancer in that area. In addition, Yu and Zhang [32] collect reports of cancer villages from academic papers and online media, summarize the present state of cancer villages in China, and analyze the relationship between the occurrence and development of cancer villages and pollution (especially water pollution) and macro-social and economic environments. The authors conclude that cancer villages, as a typical environmental health problem, are closely related to environmental pollution, especially water pollution.

To date, very little research has been performed on the temporal and spatial distribution of cancer villages. Gong and Zhang [6] reached the following conclusions: (1) Between 2000 and 2009 were "times of high occurrence of cancer villages" in China because 53% of new cancer villages appeared in that decade, and this may be related to the number of badly polluted villages caused by the large scale development of township enterprises in the 1980s. (2) The distribution model of cancer villages in China has a typical concentration with a certain regional differences effect following the river flow direction, i.e., there are more cancer villages in east China than in the central China and more in the central China than in west China, generally. Based the latest research of cancer statistics in China [33], the research shows the significant differences in cancer incidence rates for all cancers combined by place of residence (rural vs urban and between regions) in China. Rural residents have higher incidence compared with their urban counterparts, and incidence rates varied substantially across the 7 administrative regions. Besides, there are greater geographic variations in cancer mortality and the survival proxies across China. It is likely that at least part of these geographic disparities could be explained by the more limited medical resources, lower levels of cancer care, and a larger proportion of patients diagnosed with cancer at a late stage in rural and underdeveloped areas in China [34].

In our opinion, the emergence of the cancer villages is the result of the evolution of the relationship between humans and land, while its space-time distribution and its changes are a geography related health problem. However, few studies concentrate on the exploration of the space-time distribution and the relationship with adjacent cities, thus calling for additional research.

3. Description of the system

Located in the eastern part of China, the Huaihe River Basin lies between the Yellow River and the Yangtze River (111°55′E to 111°45′E, 30°55′N to 36°20′N). The Huaihe River Basin covers five provinces (Hubei, Henan, Anhui, Jiangsu, and Shandong), 35 cities, and 189 counties. The total population is about 165 million, with an average population density of 611 people/km^2, *i.e.*, 4.8-fold higher than the national average population density, thus ranking first in population density among river basins in China [35]. The total change in elevation along the 1000-km-long river course is about 200 m. The upstream and midstream portions of Huaihe River are characterized by numerous inflows, with 16 tributaries that cover >2000 km^2. Near the Huaihe River, the population has been increasing, industrial and agricultural production have experienced rapid development, and township enterprises have maintained an upward trend since the 1990s.

However, along with development of the urban economy, urban pollution is becoming an increasingly serious problem. Waste flows, such as sewage, industrial waste, urban waste, industrial residues, medical waste, pesticides and fertilizers used in farmland mostly flow along with heavy rain into rivers, resulting in severe pollution across the Huaihe River basin. Statistically, the Yinghe River and Shahe River receive waste water from >30 cities from Zhengzhou to Xiangcheng, with an average amount of up to 1.662 million tons per day. Five counties (or cities) in Fuyang, Anhui Province, discharge 138,000 tons of sewage daily, severely contaminating the Kuihe River, Xinbianhe River, and Suihe River and aggravating Huaihe River's quality. Indeed, Huaihe River water pollution has become a major societal concern in all walks of life (see Fig. 1).

3.1. Environmental quality data of surface water in the Huaihe River basin

The 2004–2006 data used for environmental quality analysis of surface water in the Huaihe River basin were obtained from the series Environmental Quality Reports (EQR) of the People's Republic of China. The annual EQRs were initially published by the State Environmental Protection Administration (SEPA) in 2004–2006. SEPA was replaced by the Ministry of Environmental Protection (MEP), so reference was made to the MEP's reports published in 2009–2010. Specifically, the water quality monitoring data for the nationally controlled sections of the Huaihe River were used for analysis, which included the water quality grades and corresponding monitoring indicators. The Huaihe River basin was divided into different sections to monitor water quality, with the number of sections varying prior to 2003 (please refer to Fig. B1:

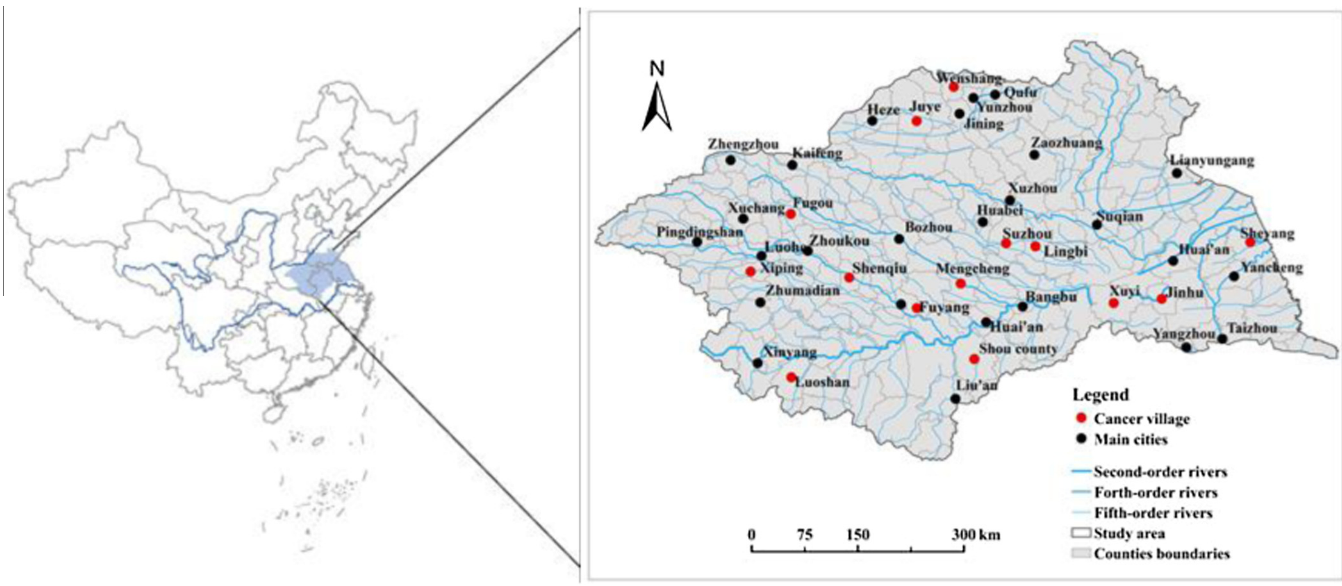

Fig. 1. The "cancer villages" in the Huaihe River Basin and the adjacent urban area (modified from Yang and Zhuang, 2013).

River system of the Huaihe River basin and its water quality monitoring sections in Appendix B). In 2003, the number of nationally controlled sections was fixed at 86, comprising 14 and 72 sections along the main river and its tributaries, respectively (please refer to the Appendix B, Fig. B1).

For the selected data, although some annual EQRs graded the water quality of the various sections, the concentration levels of the indicators used and corresponding grades were not provided. For some years, the concentration levels of the water quality indicators were directly provided instead. Water quality data that had not been graded in the EQRs were categorized based on the national water quality standards (GB3838–1988 and GB3838–2002). The main monitoring indicators used for grading water quality included ammonia/un-ionized ammonia, biochemical oxygen demand (BOD), chemical oxygen demand (COD), and volatile phenols. Un-ionized ammonia refers to nitrogen (NH_3) that exists in water in the form of free ammonia, while ammonia nitrogen is the sum of free ammonia in water and ammonium ion (NH_4^+). BOD is the total amount of oxygen dissolved in water that is used by microorganisms for oxidative decomposition of organic matter. As a result of this biological action, organic matter in the water becomes mineralized or gasified. For COD, a chemical oxidant (such as potassium permanganate) is used for oxidative decomposition of oxidizable substances in the water (including organic matter, nitrites, ferrous salt, and sulfides), followed by the calculation of oxygen consumption based on the amount of residual oxidant. Volatile phenols usually refer to phenols with boiling points <230 °C. These monohydric phenols are highly toxic substances.

For a particular section where the observational data on water quality were available for a sufficient period of time, its water quality situation would also be reflected by the number of times the Grades V–sub-V group (polluted) appeared as a ratio (frequency) of the total number of observations. That ratio was defined as the frequency of water pollution and calculated as follows:

$$FWP = Y_p/Y$$

where Y_p is the number of times that Grades V–sub-V appeared within a specific observational period, and Y represents the total number of observations (which could be on a monthly or annual basis). The water quality Grades V–sub-V referred to in the formula could be the water quality grade obtained after comprehensive evaluation or the concentration grade of a single water quality monitoring indicator. Considering some sections have incomplete data for certain years, Grades V–sub-V water quality for these sections were mainly computed using those years for which monitoring data were available. If the monitoring data for a selected section were missing for a particular year, that year was not included in the computations (see Fig. B2 in Appendix B).

3.2. Death surveillance data of the population in the Huaihe River basin, 2004–2006

In 2005, the Chinese Center for Disease Control and Prevention performed studies on malignant tumors and their related risk factors among the population of the Huaihe River basin at three key locations. In 2007, based on this study, the China CDC performed a 3-year retrospective investigation into the causes of death. A total of 14 counties along the main Huaihe River and its main tributaries were selected for the study, generating the data of the population's cause of death during 2004–2006. This investigation was a sub-section of the national survey on causes of death and epidemiology. Using the compiled data, the China CDC established a comprehensive monitoring system for the causes of death, illnesses, births, and birth defects. This system covers a population of 12.64 million, which comprised 8% of the total regional population of the Huaihe River basin at that time. The 14 counties monitored by the China CDC were distributed among six of the aforementioned zones used for our analysis of water quality, specifically the eastern downstream region, central eastern plains, western hilly and mountainous region, central western plains, southern plains, and drainage basin of Nansi Lake (see Fig. B3 in Appendix B).

The determination of causes of death for residents living in the areas being monitored were as follows: (i) for those who passed away in the hospital, cause of death was stated on the medical certificate of death filled out by the attending physician; or (ii) for those who died at home, reference was made to the hospital's diagnosis. If that hospital ranks lower than a rural hospital or when the tumor diagnosis was made by a hospital that is outranked by a

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county hospital, a trained doctor from the rural hospital used the autopsy inference scale and the residents' medical information before death to fill out the certificate for the inferred cause of death. The local county CDC then submitted the medical certificates of death and certificates for the inferred cause of death to the China CDC through a network platform of the national system for death reporting. The monitoring and analysis report for the causes of death for the population of the Huaihe River basin was completed annually.

3.3. Changes in gastrointestinal cancer deaths among the population of the Huaihe River basin

The increase in tumor mortality rates in these areas was related to changes in mortality rates by several major gastrointestinal cancers. This collection described, in detail, changes in the mortality rates of liver, stomach, and esophageal cancers within the Huaihe River basin.

- Hepatic/liver cancer

In the period of 1973–1975, incidences of liver cancer in the Huaihe River basin were low. The exceptions were the counties of Jinhu, Xuyi, and Sheyang located downstream, for which the population had a higher mortality rate from liver cancer than the national average. The mortality rate for most of the counties (districts) was lower than the national average, including those located along the Level 1 tributaries in the western plains at the mid- and up-stream portions of the Huaihe River: Shenqiu and Yingdong (on the banks of the Shaying River), Fugou and Mengcheng (Wo River), Yongqiao and Lingbi (Kui River), Xiping (Hong River), and Wenshang and Juye (located at the basin of the Yi–Shu–Si Rivers). The rates of these counties were approximately 50% of national average, with a small number of other counties being consistent with the national average (please refer to the 1973–1975 standardized hepatic cancer mortality rates for males and females, respectively).

However, the mortality rates due to liver cancer for the population of these regions was generally higher than the national average by the period of 2004–2006. This was especially so for the populations in the basins of the Shaying, Kui, and Wo Rivers, where the mortality rates were 1.45–1.86 times that of the national average. Of greater concern was that over the three decades, the increase in death rates of these populations with originally low incidences doubled that of the national average, with Shenqiu reaching 5.43 times the national average.

- Gastric/stomach cancer

Incidences of gastric cancer in the Huaihe River basin in 1973–1975 were also low. The exceptions were the counties of Jinhu, Xuyi, and Sheyang located downstream, for which the population had a higher mortality rate from gastric cancer than the national average. The mortality rates for the other regions was generally 40–80% of the national average (please refer to the 1973–1975 standardized gastric cancer mortality rates for males and females, respectively).

By 2004–2006, most of the counties (districts) that originally had low incidences of gastric cancer deaths exhibited increasing trends of rates higher than the national average. In particular, the rate for Shenqiu increased by 2.56 times compared to that in 1975. For Jinhu and Sheyang Counties, which originally had high incidences, the rates remained higher than the national average. However, the decline in rate was faster than the national average, leading to a narrower gap between the two rates.

- Esophageal cancer

In the period of 1973–1975, there were high incidences of esophageal cancer in the mid- and down-stream areas of the Huaihe River and Subei region. Certain areas on the south bank of the Huaihe River, within the river's drainage basin (in Shandong Province), and upstream (in Henan Province) also had high incidences. The low-incidence areas were located in the central eastern plains of the Huaihe River, where the rates were 60–80% that of the national average. For the populations of most of the regions, the esophageal cancer mortality rate was equivalent to or slightly lower than the national level.

Corresponding to the 14 counties (districts) being monitored, the four counties of Jinhu, Xuyi, Sheyang, and Yingdong had mortality rates higher than the national average. For the remaining cities and counties, the esophageal cancer mortality rates of the population were equivalent to or slightly lower than the national level.

In the period of 2004–2006, the mortality rates of the population in most of the regions in the 14 counties (districts) of the Huaihe River basin being monitored exhibited a downward trend, as was the case with the national level. However, the rate of decline was slower than the national rate, resulting in a higher than national level mortality rate. The mortality rates of areas originally with low or normal incidences, including Shenqiu, Shou County, Yingdong, Lingbi, and Mengcheng at the western plains along the mid- and up-stream of the Huaihe River, as well as Wenshang and Juye of the Yi–Shu–Si Rivers basin, exceeded the national average. This was especially so for Shenqiu and Yongqiao (the former Su County), where the rising rates transformed these areas from normal to high incidences of esophageal cancer. However, there was generally a downward trend in esophageal cancer mortality rates for the population of most of the counties (districts) being monitored.

4. Methods

4.1. Gravity model methods to assess economic and pollution flows between cancer villages and adjacent cities

Cancer villages are products of a certain historical stage of economic and social development, closely related to regional economic development. In addition, a high incidence of cancer has been confirmed to have a close tie to environmental pollution. Therefore, the flows between cancer villages and adjacent cities that we focused on are mainly economic and pollution relationships.

Economic relations are one of the manifestations of spatial interaction between cities. In theory, the interaction between cities is positively correlated with city scale and negatively correlated with the distance between the cities (gravity model). The gravity model was selected to calculate the economic relationships between 14 cancer areas and their adjacent big cities. The gravity model approach is often used to analyze economic performance among cities. Western regional economists and geologists have long applied Newton's gravity hypothesis in physics to the study of economic space. The law of universal gravitation states that attraction between two objects is in direct proportion to their respective qualities and inversely proportional to the distance between the two. In 1880, the English demographer Ravenstein applied the gravity model to population analysis, starting the use of Newton's gravity model to the research of social science. Reilly (date) put forward the famous Reilly Formula in the 1930s, spreading the gravity model to field of social economy in a real sense. That formula was applied so widely in economy and society that classical textbooks referred it as Reilly's Law of Retail Gravitation [10]. American geographer Tobler [36] developed a gravity model

Table 1
Main methods and indices of ENA methodology.

Analytic method	Goals and applications	Indices
Throughflow analysis	Calculates the flow parameters of material and energy of each compartment within the ecosystem	TST, APL, FCI, etc.
Structural analysis	Represents interconnection patterns between compartments in digraph or adjacency matrix	Pathways numbers, pathway length
Storage analysis	Identifies non-dimensional storage intensities along indirect pathways	Storage mass, retention time
Utility analysis	Analyzes the direct and indirect relationships between components and the mutualism they perform of the concerned ecosystems	Integrated mutualism index, synergism rate
Control analysis	Analysis of the control each component exerts in the overall system configuration	Flow dependency, control distribution
Trophic (food web) analysis	Calculates the trophic level of species and identifies the existence of cycles within the ecosystem	Integrated trophic level, trophic chains
Information-theoretical analysis	Quantifies the performance (like development status, diversity and maturity) of the system as a whole at processing material and energy	Developmental capacity, ascendancy, overload, redundancy

measuring economic relation performance among cities based on Newton's gravity model. According to this model, the interaction between different cities (*i.e.*, the economic relation performance) is proportional to the two cities' social and economic scale and is inversely proportional to the square of the distance between the cities. Since then, a number of scholars have revised each of the parameters in the model on the basis of practical problems, continuously improving and applying this model. Several scholars in China also use the interaction force in this model to perform a large number of empirical analyses, verifying that the economic relation performance between cities is influenced by economic scale and their distance. With the gravity model approach, Gu and Pang [37] conducted a quantitative calculation of space intensity between Chinese cities, describing the space link and nodule area structure of China's urban system. Tang et al. [38] measures the economic relation performance and the strength of economic linkage between different cities in the Huaihai economic zone based on the gravity model and the model of integrated passenger transportation. Additionally, they analyze the urban economic radiation and membership. Using the potential model, Xue (2008) divides the economic impact area of 31 provincial capitals in China, sums their overall distribution characteristics, and studies the composition of different economic impact areas and their distribution across the provinces. The authors comprehensively analyze the provincial capitals' economic impact areas and provincial administrative scope and conclude that there are four types of spatial relationships. Based on the economic potential model, Wu (2010) performed a study on the comprehensive transportation planning of Shanghai and Ningbo, providing a development model and reference for other urban and economic transportation projects.

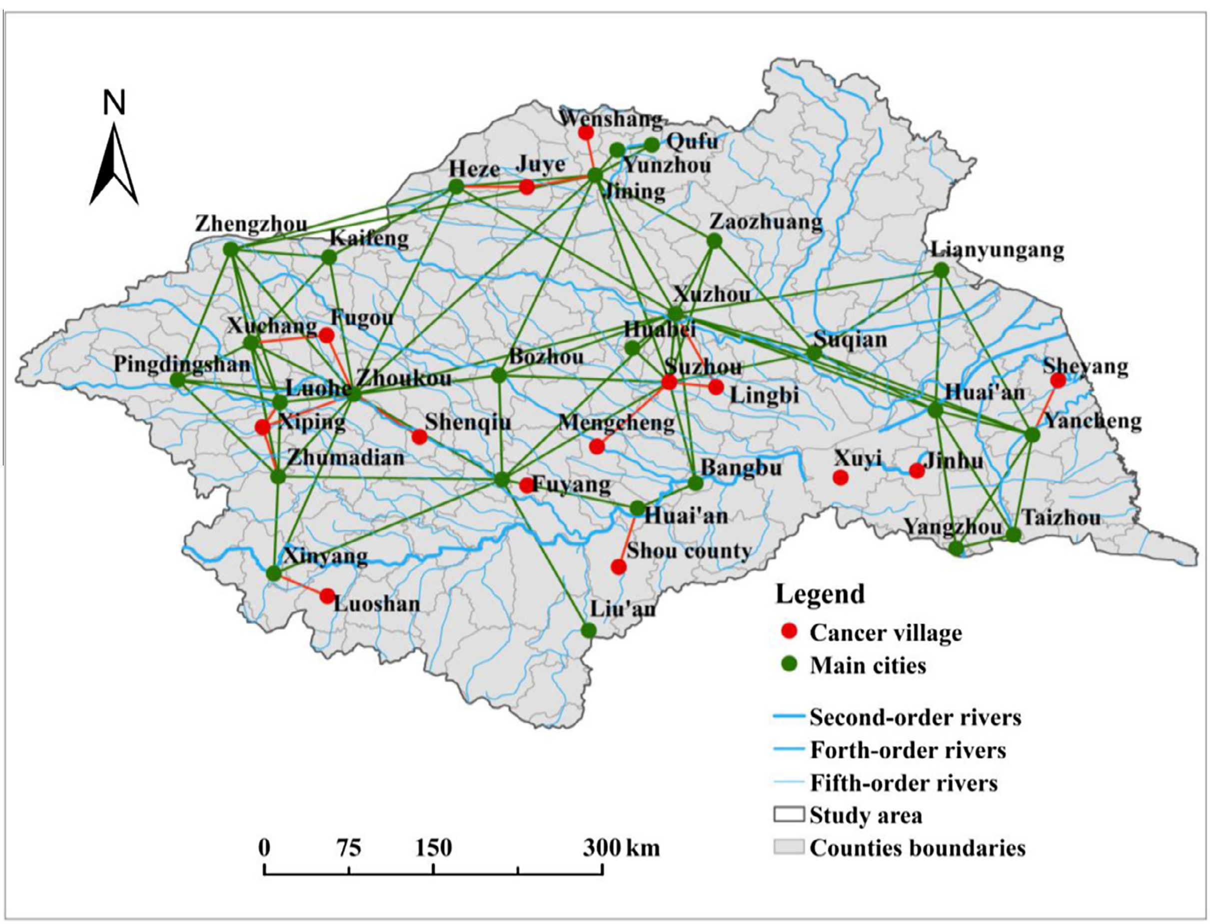

Fig. 2. Extremely strong economic relationships between "cancer villages" and adjacent cities in Huaihe River Basin ($R_{ij} \geqslant 10$) (calculated data, see Table 1A in Appendix).

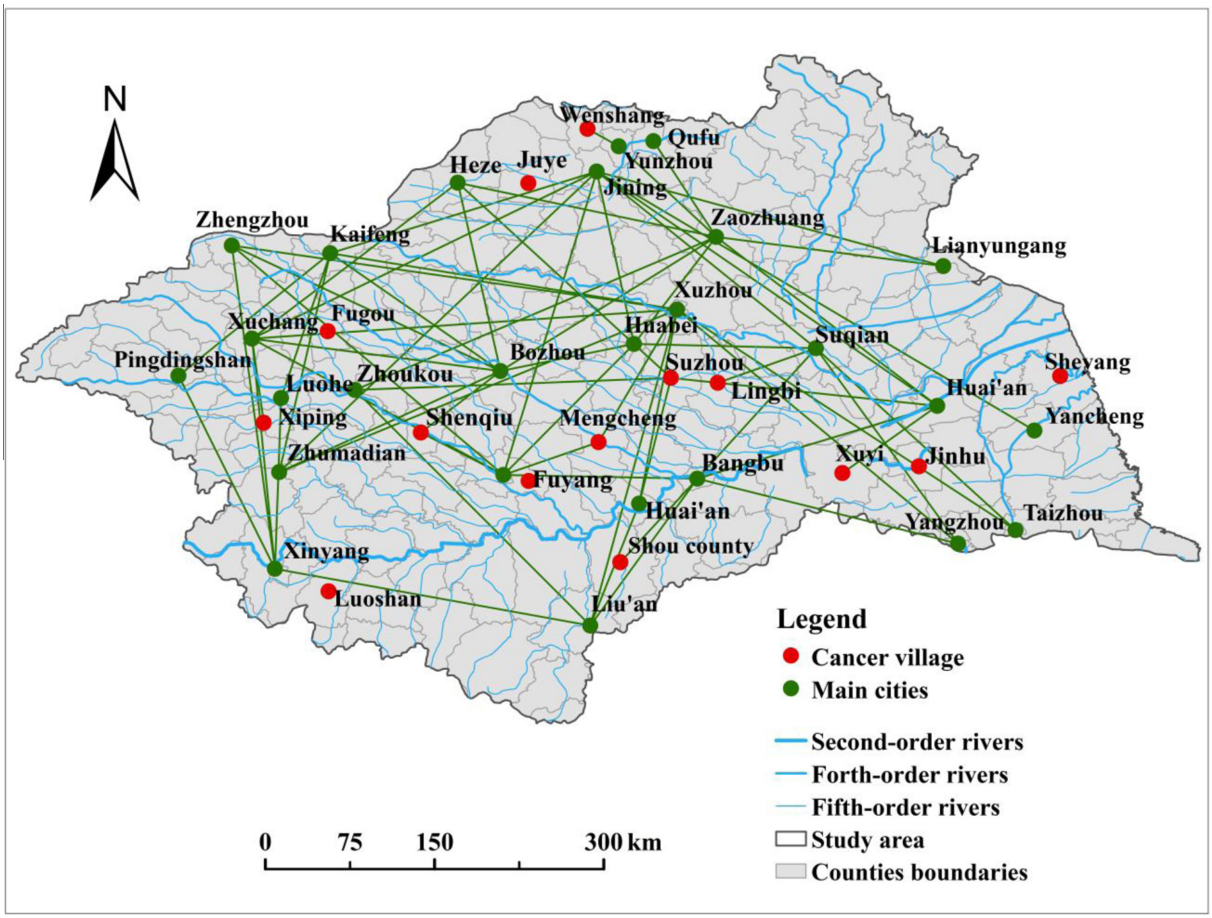

Fig. 3. Weak economic relationships between "cancer villages" and adjacent cities in Huaihe River Basin ($0.5 \leqslant R_{ij} \leqslant 5$) (calculated data, see Table 1A in Appendix).

In this study, the gravity model is usually expressed as:

$$I_{ij} = GP_iP_J/d_{ij}^r \tag{1}$$

where I_{ij} refers to the gravity between the two cities (i and j), P_i and P_j refer to the "city quality", d_{ij} refers to the distance between the two cities, G refers to the gravity coefficient, and r refers to the gravity attenuation coefficient (in most cases = 2) [39].

In practice, the gravity coefficient G has no correlation with urban economic gravity, but the contents of P and d must be redefined, which affects the entire formula. Therefore, the expression is restructured as:

$$I_{ij} = P_iP_j/d_{ij}^2 \tag{2}$$

In this expression, P_i and P_j can be measured by different methods, and we selected a single index to measure "city quality", such as GDP, N (total population), V (pollution degree). Here, we use $P = \sqrt{GDP \times N}$ [40].

Specifically, the following formula shows the calculation of economic relation and the pollution relation:

$$R_{ij} = (\sqrt{GDP_iN_i} \times \sqrt{GDP_jN_j})/d_{ij}^2 \tag{3}$$

where i refers to one city (No. 1), j refers to the other city (No. 2), R represents the economic relationship between the two cities, N refers to the city's population (unit = ten thousand), GDP refers to the annual gross domestic product (unit = one hundred million *Yuan*), and d refers to the distance between the two cities (unit = km).

What an economic relationship means is that when cities No. 1 and No. 2 have some economic linkage, they affect each other's economic conditions, and the economic relationship is used to represent the strength of the ties. Obtaining the specific numerical value of the economic relationships between the 14 monitored counties and the adjacent cities, the data can be used in a matrix of the economic relationship, and GIS technology can be used to generate a distribution diagram for the economic relationships in the targeted research areas.

Similarly, we used the gravity model to determine the pollution relationship between cancer villages and their adjacent cities. We input the interpreted data of urban pollution, population data, and the distance from cancer villages to their adjacent cities into the gravity model to measure this relationship using the formula:

$$S_{ij} = \left(\sqrt{V_iN_i} \times \sqrt{V_jN_j}\right)\Big/d_{ij}^2 \tag{4}$$

where i refers to one city (No. 1), j refers to the other city (No. 2), S refers to the pollution relationship, N refers to the city's population (unit = ten thousand), V refers to the pollution degree, and d refers to the distance between the two cities (unit = km).

4.2. Methodology for assessment of cancer villages based on Ecological Network Analysis (ENA)

Since Hannon, Patten, and Finn first published their papers on the analysis of flows in ecological networks (Hannon 1973; Finn, 1976; [41], there have been multiple studies of methods for and applications of ecological network analysis. Among them, Ulanowicz [42], Ulanowicz [43] emphasized a combination of transactive

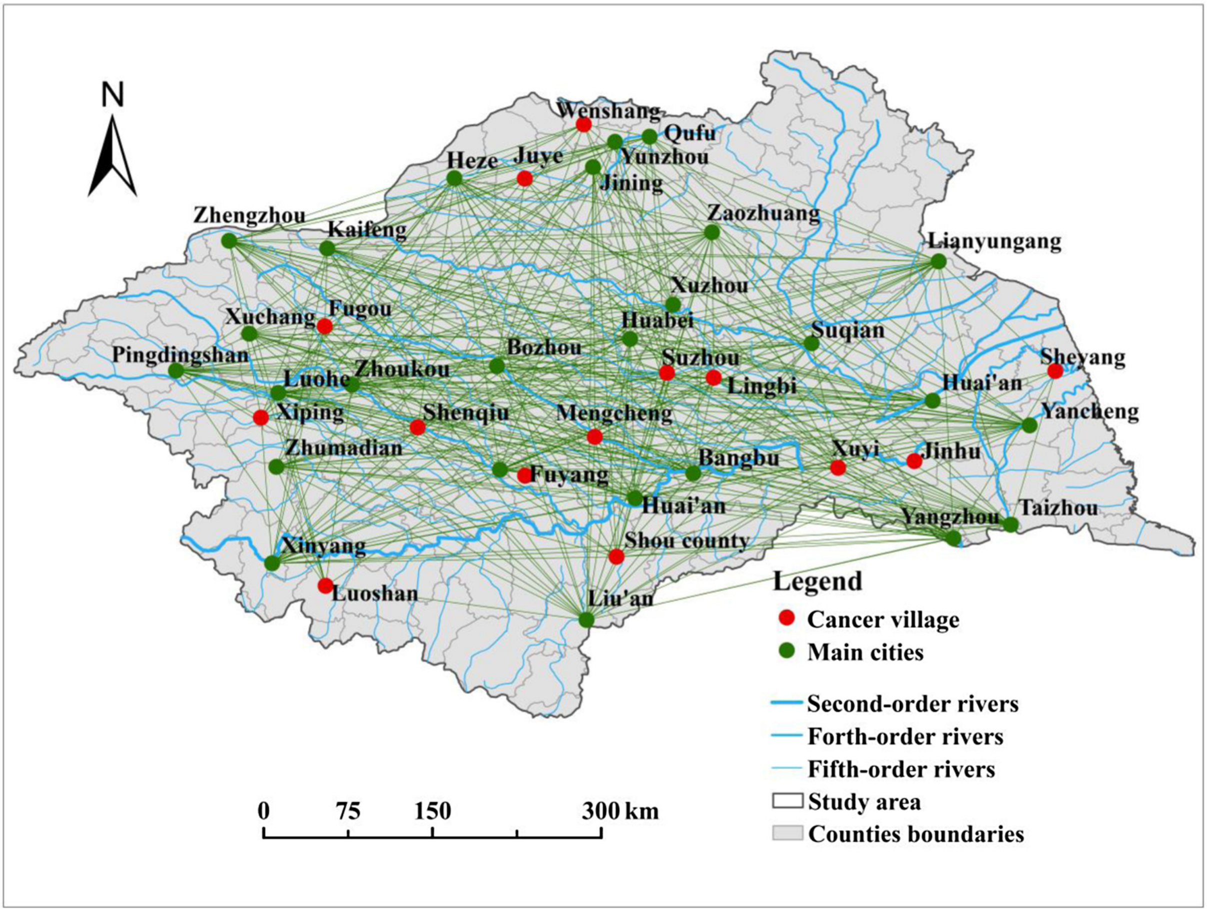

Fig. 4. Negligible economic relationships between "cancer villages" and adjacent cities in Huaihe River Basin ($R_{ij} < 0.5$) (calculated data, see Table 1A in Appendix).

Table 2
Extremely strong economic scores between "cancer villages" and adjacent cities in Huaihe River Basin.

	Wenshang	Juye	Fugou	Xiping	Shenqiu	Luo	Mengcheng	Lingbi	Shou	Xuyi	Sheyang
Jining	50.21	32.39	0.80	0.67	1.20	–	1.47	1.49	0.76	0.66	–
Qufu	2.66	0.85	–	–	–	–	–	–	–	–	–
Yanzhou	6.30	1.61	–	–	–	–	–	–	–	–	–
Heze	3.55	11.45	1.14	0.72	1.18	–	0.88	0.65	–	–	–
Zaozhuang	1.97	1.85	–	–	0.60	–	1.17	1.80	0.57	0.62	–
Xuchang	–	0.51	10.16	6.58	2.30	0.59	0.60	–	–	–	–
Zhoukou	0.67	0.96	13.23	12.49	34.14	1.71	2.38	0.88	1.20	–	–
Pingdingshan	–	–	1.70	4.18	1.14	0.52	–	–	–	–	–
Kaifeng	0.52	0.82	2.91	1.10	1.11	–	–	–	–	–	–
Zhengzhou	0.73	1.01	4.02	2.53	1.76	0.52	0.72	–	–	–	–
Luohe	–	–	3.23	39.61	1.96	0.53	–	–	–	–	–
Zhumadian	–	–	2.22	26.33	4.47	3.31	0.96	–	0.72	–	–
Haozhou	0.53	0.81	1.15	0.94	5.01	–	3.42	1.04	1.02	–	–
Fuyang	–	–	0.81	1.36	5.86	1.44	7.02	3.05	4.43	0.58	–
Xinyang	–	–	0.71	2.40	1.86	19.25	0.79	–	0.74	–	–
Suzhou	0.53	0.64	–	–	1.18	–	11.61	10.57	2.30	1.12	–
Bengbu	–	–	–	–	0.56	–	3.76	4.97	5.46	1.93	–
Huaibei	–	–	–	–	0.61	–	2.79	2.28	0.68	–	–
Xuzhou	2.09	2.36	0.76	0.76	1.80	–	5.83	13.35	2.31	2.32	–
Suqian	–	–	–	–	–	–	1.21	5.17	0.79	2.57	–
Luan	–	–	–	–	0.73	0.65	1.34	0.71	3.79	0.56	–
Yangzhou	–	–	–	–	–	–	0.68	1.08	0.81	3.92	0.77
Huaiyang	–	–	–	–	–	–	0.87	2.28	0.74	5.88	1.43
Taizhou	–	–	–	–	–	–	0.51	0.78	0.57	2.15	1.01
Yancheng	–	–	–	–	–	–	0.78	1.17	0.65	2.55	13.68
Huainan	–	–	–	–	0.53	–	3.14	1.46	44.33	0.75	–
Lianyungang	–	–	–	–	–	–	–	0.96	–	0.91	0.95

Table 3
Maximum, minimum, and average distances of economic relationships in the "extremely strong" level.

Unit: km	Average distance of economic relationships
Minimum	20.79
Maximum	78.10
Average	48.24

flows (i.e., energy or matter) and information theory called ascendancy; he also used network analysis to investigate mixed trophic levels and relational interactions between components [44]. Patten [45] and colleagues developed a branch of ecological network analysis called Environ Network Analysis (ENA), and analyzed indirect effects [46], network amplification [47], network homogenization [47,48], and network synergism [45,49] applying this method. The ecological network analysis research bifurcated into two self-similar, yet independent sub-areas, environ analysis and ascendancy analysis [50], both capable of quantifying direct and indirect ecological relationships within the ecosystem.

The two methods mentioned above construct the theoretical underpinning of ENA, and the related analysis methods and indices have been addressed explicitly [42,44,50–54], including network structural analysis and functional analysis (throughflow analysis, utility analysis, control analysis, information-theoretical analysis etc.). The methods and indices derived from ENA are listed in Table 1.

These methods and concepts composing ENA have not only been widely used in the study of specific ecosystems, but also extended into other realms, such as social and economic systems [52,53]. ENA has proved an effective and explicit technique for analyzing the structural and functional properties of the system as a whole [55–60], thus may reflect the changed condition of the environment by human disturbance.

The methodology for network utility analysis is described in following literatures [45,49,53], which gives us a direct net flow matrix $D = D(F)$ based on the steady net flows between compartments normalized by the compartmental throughflow such that $d_{ij} = \frac{f_{ij}-f_{ji}}{T_i}(j, i = 1, \ldots n)$. In addition to the direct relations proceed directly between two compartments. The integral utility matrix U, which describes the contribution of all direct and indirect relations, is found by summing all powers of D:

$$U(F) = \sum_{m=0}^{\infty} D(F)^m = (\mathrm{I} - D(F))^{-1} \tag{5}$$

The result is useful because the signs of **U** provide the integral relations between network nodes (which may vary from the direct relations) and the overall sign comparisons classify the network according to the degree of mutualism. We calculate a utility function $J(\mathrm{F})$ as a share of positive relations in sign(**U**).

$$J(F) = \frac{S_+(F)}{S_-(F)} \tag{6}$$

where $S_+(F)$ is the number of all positive relations, and $S_-(F)$ is all negative relations in matrix $U(\mathrm{F})$ [61]. Thus, J(F) characterizes the ratio between the number of all positive and all negative relations. We consider J(F) as a goal function related to network mutualism in the energy system [49]. When J(F) > 1 mutualism occurs, indicating

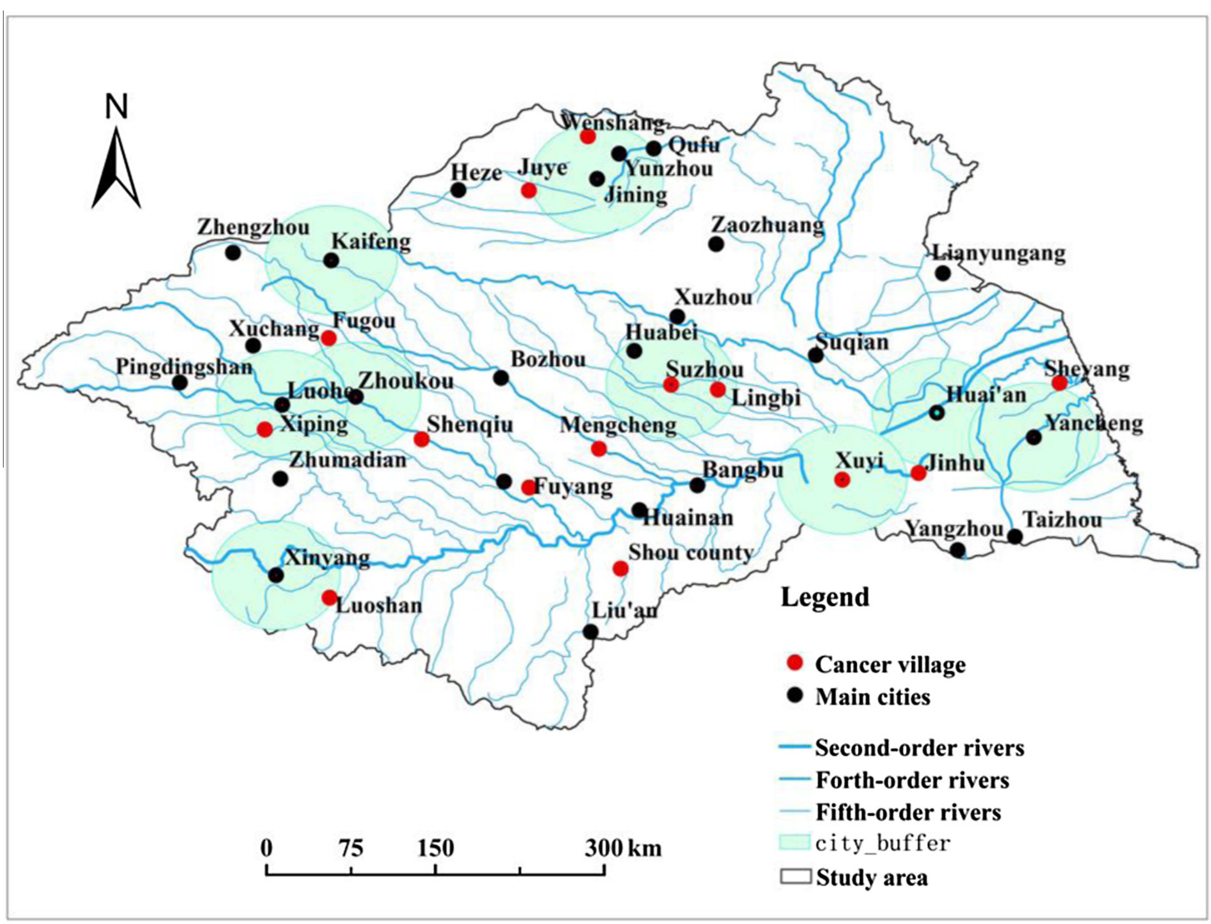

Fig. 5. Influence range of big cities (radius = 48.24 km).

that the system overall has more positive sign-pair relations than negative ones.

5. Results

5.1. The economic relationship between cancer villages and adjacent cities

From pollution data, economic data, and the above calculation procedures, we obtained the economic relationships between 12 high-risk areas of cancer along the Huaihe River, the economic relationships between high-risk areas of cancer and large- and medium-sized cities near the Huaihe River, and the year 2010 matrix of the economic relationship R_{ij} (see Table 1A in Appendix). Although the number of cancer villages in the Huaihe River Basin is 14, only 12 will be discussed when analyzing the economic relationships between them and adjacent cities because the Yongqiao and Yingdong areas lack economic data, and Jinhu County lacks pollution data. GIS visualization technology was adopted to generate a distribution diagram of the remaining 12 high-risk cancer areas and the adjacent urban economic relationships (see Figs. 2–4). The economic relationship is defined as follows: $R_{ij} \geqslant 10$ stands for "extremely strong", $5 \leqslant R_{ij} \leqslant 10$ stands for "strong", $0.5 \leqslant R_{ij} \leqslant 5$ stands for "weak", and $R_{ij} < 0.5$ is negligible. This self-defined classification method was used to divide the different levels.

As it can be seen in Figs. 2–4, the differentiation of economic relationships across space is evident, and the degree of economic relationships varies significantly. The influence intensity of the cities near the high-risk cancer areas is in close correlation with distance and urban scale (economic development level and population). One high-risk cancer area may be affected by the influence from more than one adjacent city (see Table 1A in Appendix). For example, Juye County in Shandong Province is highly affected by the economic influence of Jining and Heze, quantified around 32.39 and 11.45 units respectively (unit = one hundred million RMB × ten thousand people/km^2). Xiping County in Henan Province, as a more typical example, is surrounded by three cities (Luohe, Zhoukou, and Zhumadian). Its economic influence also fully embodies the cities' influence on cancer villages: the economic relationships of Xiping with these three cities are 39.61, 12.49, and 39.61 units, respectively (see Table 1). Simply put, a high-risk cancer area can be affected from several adjacent cities. Moreover, a large city may also emit influence to a number of cancer areas, for instance, Suzhou in Anhui Province economically affects two cancer areas: Lingbi County and Mengcheng County. Similarly, Jining also exerts effects on the cancer villages in Wenshang County and Juye County. From the distribution diagram, we can clearly see that the distance from Jining to Wenshang and the distance from Jining to Juye is the same, similar to the distance from Suzhou to Lingbi and Suzhou to Mengcheng. Through concrete data comparison, the distance from Jining to Wenshang and the distance from Jining to Juye is 36.48 and 44.73 km, respectively; the distance from Suzhou to Lingbi and the distance from Suzhou to Mengcheng is 56.25 and 56.35 km, respectively. Thus, we can further hypothesize that a big city's impact on adjacent small cities and even counties can be represented by a circle with

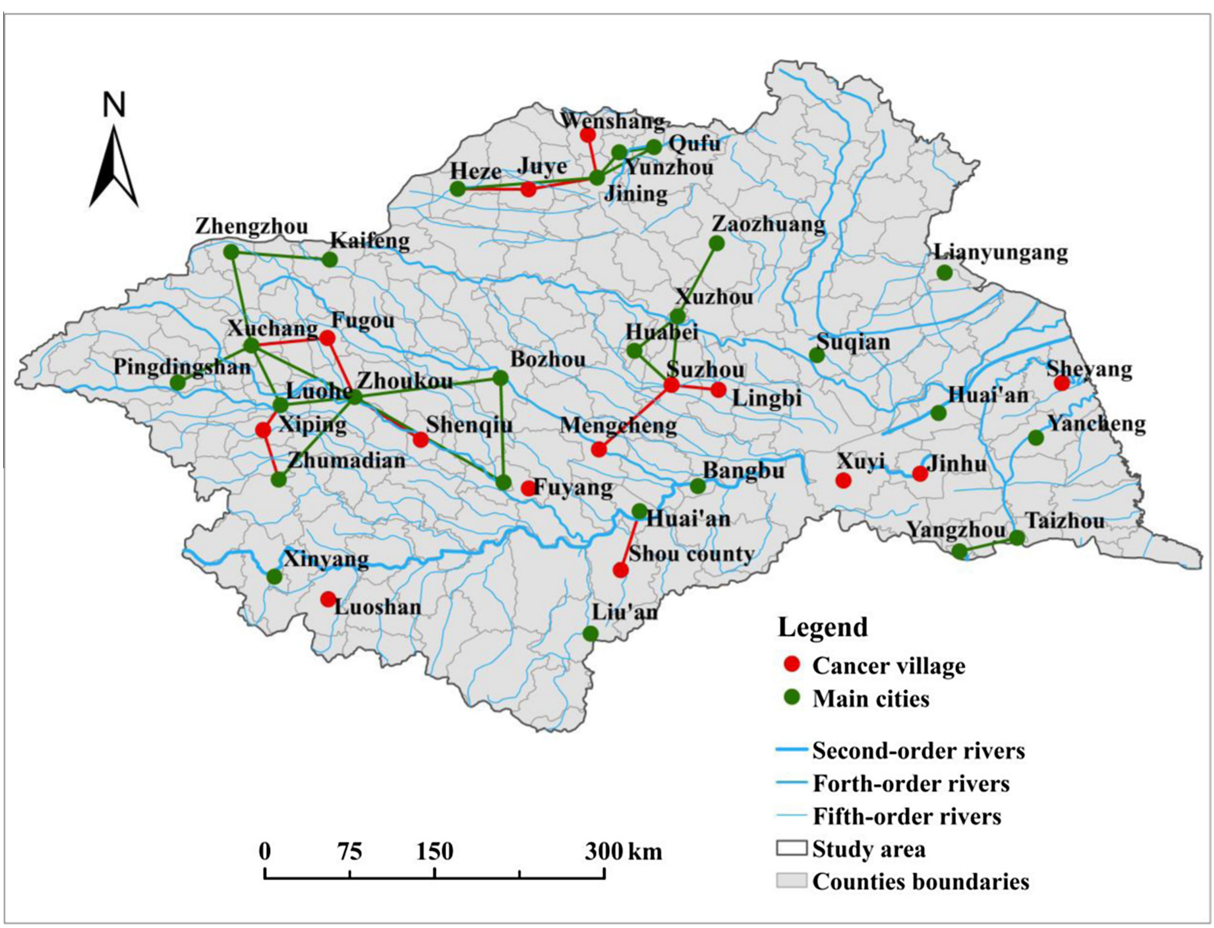

Fig. 6. Extremely strong pollution relationships between "cancer villages" and adjacent cities in Huaihe River Basin ($S_{ij} \geqslant 0.05$) (calculated data, see Table 4A in the Appendix).

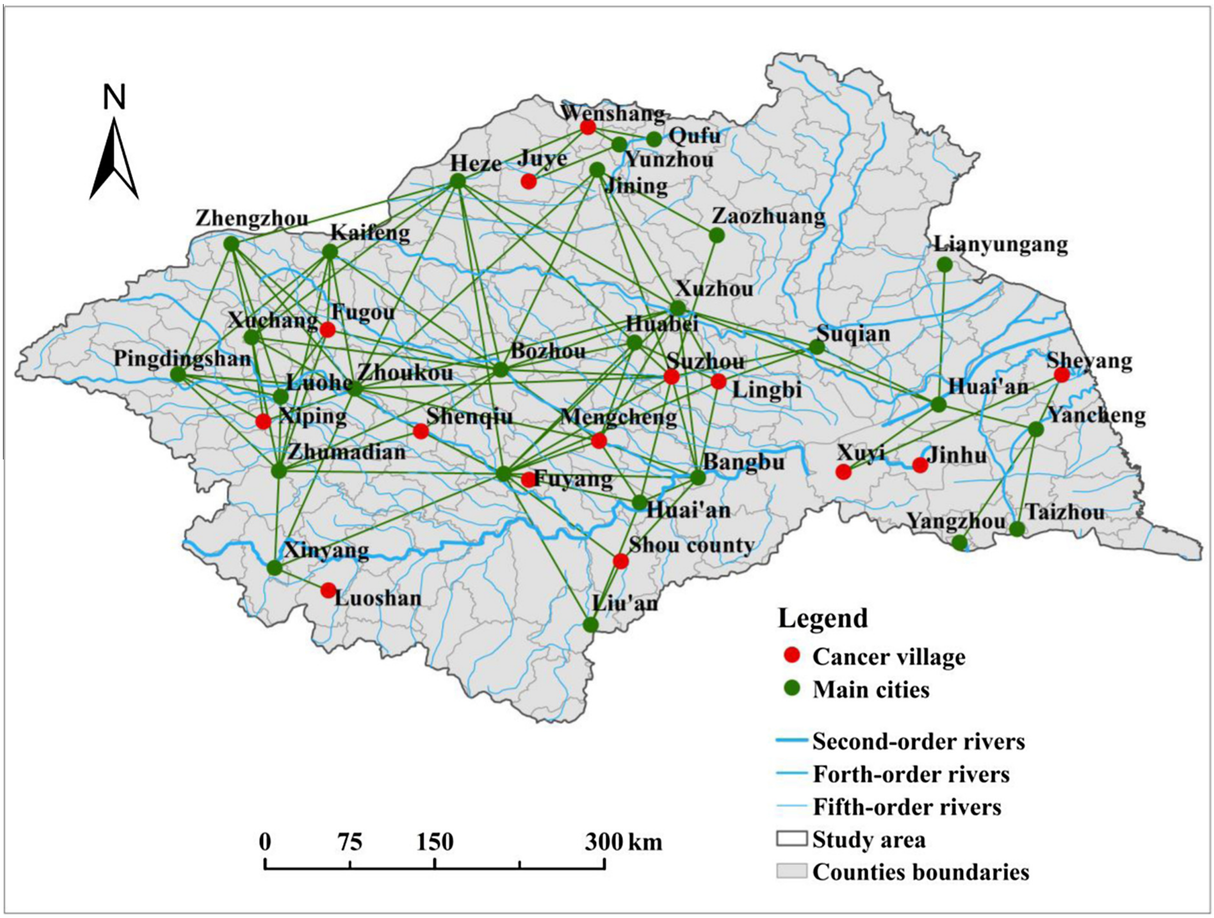

Fig. 7. Strong pollution relationships between "cancer villages" and adjacent cities in Huaihe River Basin ($0.01 \leqslant S_{ij} \leqslant 0.05$) (calculated data, see Table 4A in the Appendix).

a certain radius expressing its economic and environmental influence. This is confirmed by the case of three cancer villages in the economic radiation area of Zhoukou in Henan Province (Fugou County, Xiping County, and Shenqiu County) among which Shenqiu has received much media attention. The distances from Zhoukou to Fugou County, Xiping County, and Shenqiu County are 55.78, 68.08, and 44.41 km, respectively (see Table 2), with an average distance of 56.09 km. The economic relationships are 13.22, 13.22, and 12.49 units, which conforms to the "extremely strong" scope of economic relationships described above.

According to these results, the maximum, minimum, and average distance of economic relationships in the "extremely strong" level were measured in this study. Circles were drawn with major cities at the center and 48.24 km as the radius on the map of the Huaihe River Basin, as shown in Table 3 and Fig. 5. It is found that almost all cancer villages are included in the circles. Thus, villages and counties within the distance of 48.24 km from big cities are significantly affected.

Regarding the economic relationships between each pair of cities, the nearer the two cities are, the larger the economic value, population, and economic relationships. Thus, they have a closer economic relationship. For instance, Jining in Shandong Province exerts the greatest economic influence on the two monitored counties because it has the largest population and economic performance. On the other hand, though Qu Fu and Yanzhou are separated by the same distance as Jining to Wenshang, the two cities are less developed than Jining and hence have no such intense exertion as Jining to the adjacent smaller cities or counties. Furthermore, the reason why the economic relationship between of Heze and Wenshang significantly differs from the one with Juye is that the two monitored counties differ in their distance to Heze: the distance from Heze to Juye is one-half that from Heze to Wenshang. Therefore, the economic radiation of Heze to Juye is "extremely strong", while its radiation to Wenshang is "weak". The economic relationship performance score of Juye is three times as large as that of Wenshang (see Appendix Table 1A).

Through the analysis of the data in Tables 2A and 3A of Appendix, we found that there are 14 high-risk cancer areas and counties. Excluding the Yingdong and Yongqiao areas that lack sufficient economic and population data, about 81.8% of the remaining 10 areas and counties of cancer influence within 50 km of adjacent cities have economic relationships characterized as "extremely strong".

5.2. The pollution relationship between cancer villages and adjacent cities

Based on the cancer villages' economic relationships with adjacent cities, we hypothesized that the reason why malignant tumor diseases happen frequently may be strictly correlated to the pollution of the adjacent environment because environment pollution can spread to these areas and counties through the air, soil, and surface water. This leads to accumulation of the pollutants, resulting in higher cancer incidence. We calculated the pollution relationships between high-risk areas of cancer and large- and medium-sized cities near the Huaihe River and the year 2005 matrix of the economic relationship S_{ij} (see Table 4A in Appendix). The pollution relationship is defined as follows: $S_{ij} \geqslant 0.05$ stands for “extremely strong”, $0.01 \leqslant S_{ij} \leqslant 0.05$ stands for “strong”, $0.005 \leqslant S_{ij} \leqslant 0.01$ stands for “weak”, and $S_{ij} < 0.005$ is negligible.

As can be seen from Figs. 6–8 and Table 4A in Appendix, the pollution relationships of high-risk cancer areas to adjacent cities vary significantly. The closer two cities are, the stronger pollution relationships exist. For example, the distance between Xuchang and Fugou is ∼50 km, with a pollution relationship >0.05 (“extremely strong”). Thus, distance exerts an important influence on the intensity of pollution relationships, and only sufficiently close cities have close direct pollution relationships. Cities with a higher degree of pollution tend to greatly affect the adjacent cities, such as Xuchang’s and Zhoukou’s pollution influencing Fugou. The pollution degree in Xuchang is 0.61 and in Zhoukou is 1.00. With the same distance to Fugou, the pollution radiation of Xuchang to Fugou is 0.05 and that of Zhoukou to Fugou is 0.08. Therefore, cities with a higher degree of pollution are more likely to generate a larger pollution radiation to adjacent cities.

According to this analysis, we can see that areas and counties with a distance of <50 km from big cities tend to be greatly influenced by the city economy. Applying this conclusion to pollution relationships (*i.e.*, comparing the distance between cancer villages (see Table 2A in Appendix) and the adjacent cities with the data of “extremely strong” pollution relationships (see Table 5A in Appendix)), we sought to determine if the scope of the “extremely strong” pollution relationship was still the about 50 km identified for economic relationships. Results indicates that 63.6% of big cities reach an “extremely strong” degree of pollution relations with a distance of 50 km from the 10 high-risk cancer counties. Table 3 shows the pollution relationship matrix of 38 cities and counties by means of the gravity model. We expanded the range from big cities to analyze and select the most appropriate distance when considering pollution relationships.

The maximum, minimum, and average distance of “extremely strong” pollution relationships was measured. Compared to Table 3, we found that the difference between maximum and minimum distances characterized by “extremely strong” pollution relationships is smaller than the difference between maximum and minimum distances characterized by “extremely strong” economic relationships, as is the average distance. This phenomenon is likely due to the fact that pollution degree data are much scarcer than economic strength values, thus generating rather smaller values when calculating the pollution relationships. To conclude, within the same distance, the number of “extremely strong” economic relationship cancer villages is greater than the number of “extremely strong” pollution economic relationship of cancer villages.

In addition, Figs. 6–8 also indicates that there is no large-scale city around Xuyin County and Jinhu County. The nearest big city to Xuyin County is Huaian, with a distance of 72.73 km; the distance from Huaian to Jinhu County is 65.12 km. Further, the economic scale and population is not very large in Huaian, and its pollution is not serious (pollution level = 0.39). On the map, however, river systems are widely distributed near Xuyin County and Jinhu County. Jinhu County is surrounded by Baimahu Lake, Baoyinghu Lake, and Gaoyouhu Lake, with the Huaihe River flowing through the area. Hongzehu Lake lies to the east and north of Xuyin County, with the Huaihe River flowing through the area. Therefore, aside from the causes of higher incidence of cancer, as well as its polluted environment, we should also take into consideration the

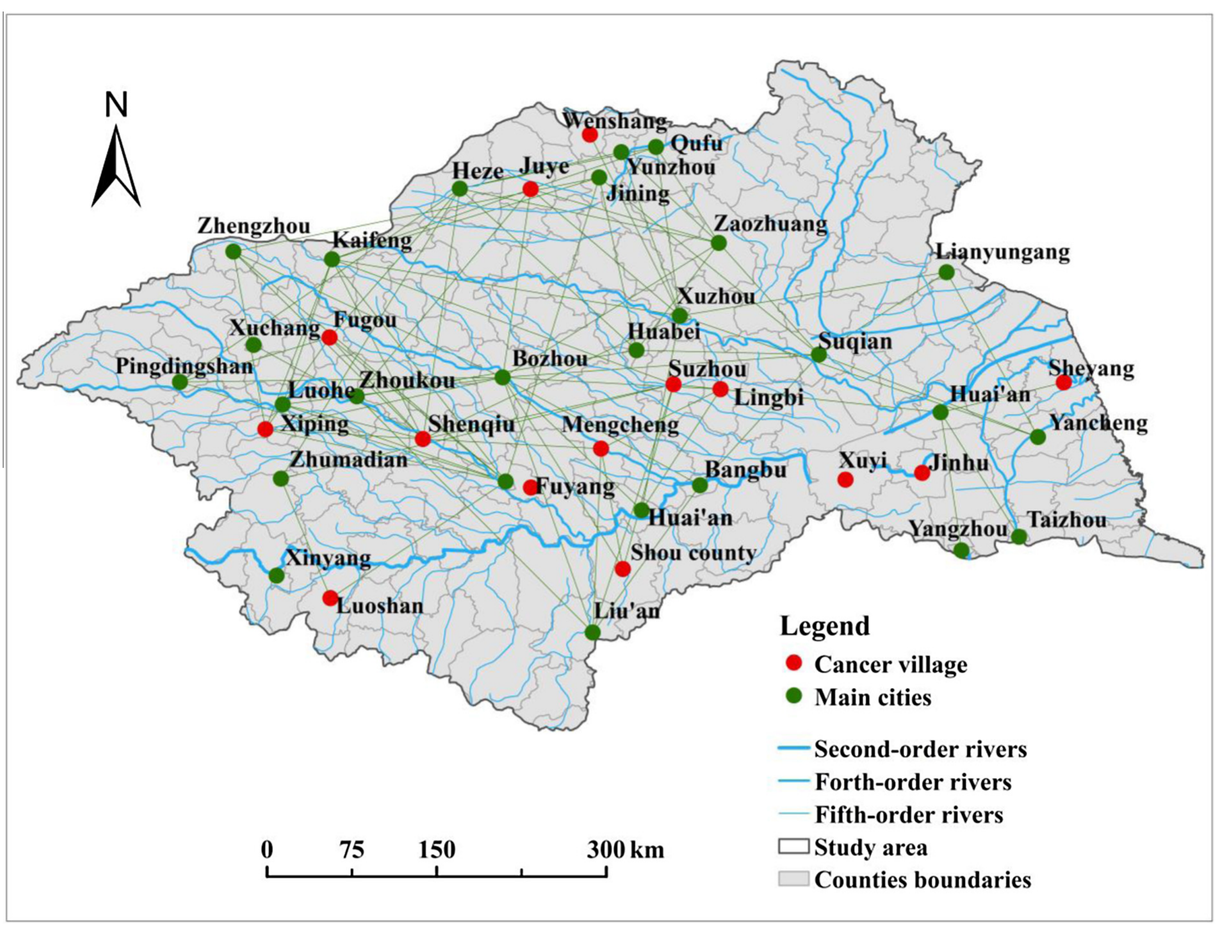

Fig. 8. Weak pollution relationships between “cancer villages” and adjacent cities in Huaihe River Basin ($S_{ij} < 0.005$) (calculated data, see Table 4A in the Appendix).

rich water resources in these counties with more possibility of serious water pollution than other counties. Once the Huaihe River and its tributaries are contaminated, they will pose a threat to the drinking water of the two counties and cause a higher incidence of malignant tumors.

5.3. The relationship between cancer villages and rivers

A buffer zone with a radius of 3, 5, or 10 km in rivers on and above the national fifth level in the Huaihe River Basin was drawn. An intersection tool was used to calculate the area of the 14 cancer villages falling within the buffer zone, and its percentage of the total area of the county was calculated. In Fig. 9, the results demonstrate that the 14 cancer villages falling within the 3-km buffer zone account for 20% of the total, those within the 5-km buffer zone account for 50%, and those within the 10-km buffer zone account for >80%. Although there are a few rivers above the fifth level in Wenshang County and the area located in the buffer zone is relatively small, its area reaches 30%. In the 10-km buffer zone, Xuyi County and Jinhai County are among the highest proportion (95.8% and 89.9% respectively), which is related to their geographical positions. As with the analysis above, there are numerous drainage sources near Xuyi County and Jinhai County, and therefore, they tend to present a higher area proportion within the 10-km buffer zone. About 80% of the cancer villages' area falls within the 10-km buffer zone indicating that the distribution of cancer villages is closely related to the distribution of rivers.

In addition, according to pollution data in various counties along the Huaihe River, we found that cities in the midstream and downstream portions of the Huaihe River are more seriously contaminated than those upstream, and that there are more cancer villages in the midstream and downstream portions than upstream. Therefore, we inferred that this may due to the fact that industrial pollution emissions increase with the development of the cities, and cause river pollution and environmental and human health impacts. Pollutants will constantly flow with the river to low-lying areas and do larger harm to the health of the people in such areas (*i.e.*, midstream and downstream). There are 10 cancer villages in the midstream and downstream portions of the Huaihe River (Wenshang, Juye, Mengcheng Shouxian, Lingbi, Yongqiao, Yingdong, Xuyi, Sheyang, and Jinhu), while there are four cancer villages upstream (Fugou, Xiping, Shenqiu, and Luoshan). Rivers, therefore, seem closely related to the distribution of cancer villages, and it is more likely for malignant tumor diseases to occur in the midstream and downstream portions.

5.4. Economic utility analysis

With the help of a utility relation table, we determined the direct and indirect relationships between cancer villages and their

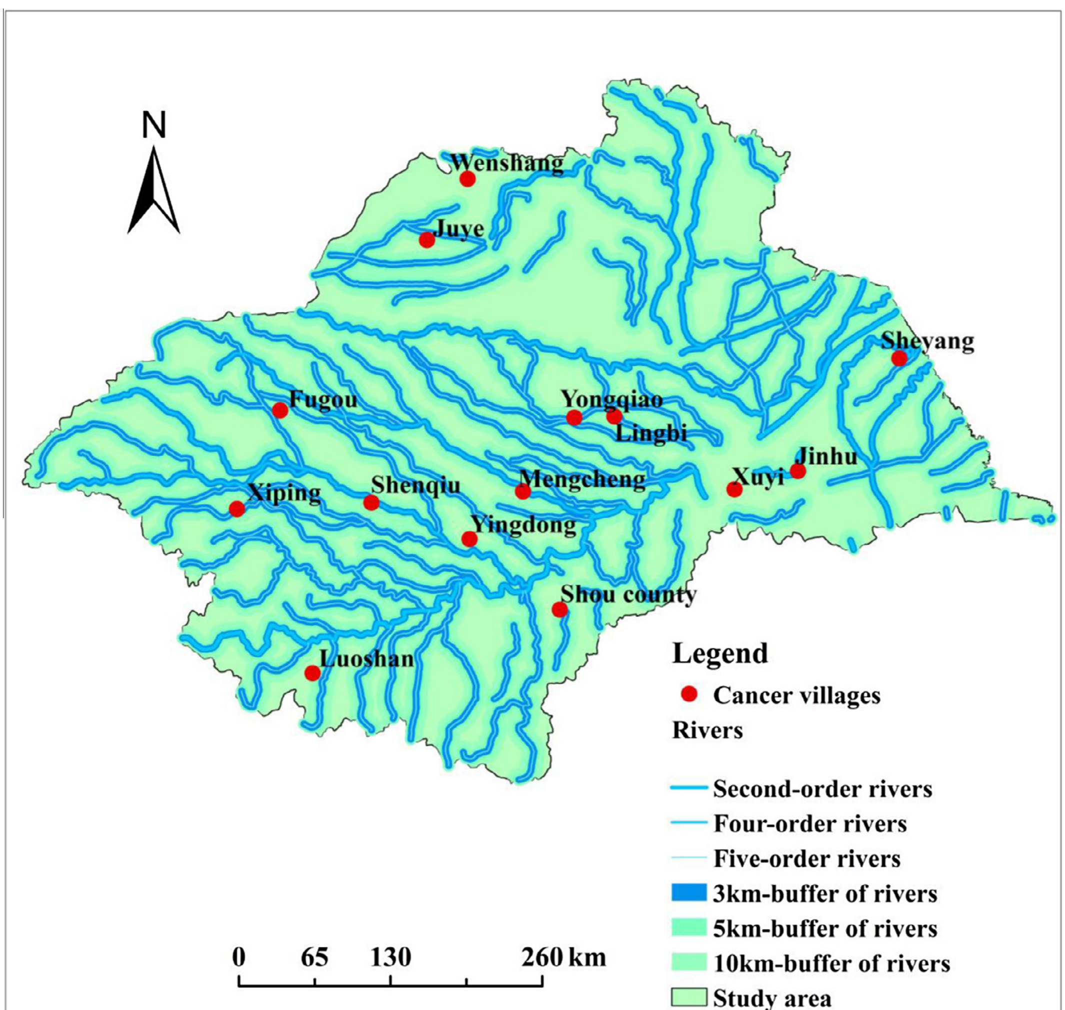

Fig. 9. About 80% of the cancer villages' area falls within the 10-km buffer zone.

adjacent cities. In biology, direct interactions over conservative resources (energy, nutrients, water, etc.) are zero-sum, meaning they are either (+, −), (−, +) or (0, 0). The first two represent transfer from one (whichever has the minus) to the other (whichever has the plus), and the last represent neutralism where the two do not directly interact. Out of these direct interactions emerge indirect and integral relations, which can still include (+, −), (−, +) and also (+, +), (−, −), representing mutualism and competition, respectively. Systems are well connected enough that null or zero relations are not exhibited. Although this definition is mainly used for species, it appears it can be used to describe the relationship among cities, and political, social, or economic exchanges between individuals and groups as well. Thus, as long as the premise of interaction exists, there are gains and losses of interests of the related participants.

With general flow matrix F, we established a direct utility matrix D (see Table 6A in Appendix, and Fig. 10) and Sgn (D) matrix (see Fig. 11) and compared the direct relationship between any two nodes across the main diagonal of the matrix. For example, (sd(12, 1), sd(1, 12)) = (−, +) indicates an "exploited relationship". So Wenshang's economy is exploited by Jining. In addition, in Fig. 10, one can observe that the economic relationships indicate that all big cities affect cancer villages, while counties have no contribution to the economy in big cities. There are direct economic relationships between cities and counties, as well as between counties. For example, (sd(6,1), sd(1,6)) = (+, −) shows that there is a direct economic relation between Luoshan County and Wenshang and that Luoshan plunders Wenshang's economy. The SD matrix has the same number of plus and minus signs because all of the nodes are either inputs or outputs.

Fig. 11 shows the integral utility matrix Sgn(U) – from Eq. (1), in which the dark red element is a "+" relationship, while the light red element is the "−" relationships. The results show that there are some differences in matrix U. Only several counties' elements add up to zero in the general matrix, and the rest in the U matrix are not zero, indicating that all nodes have direct or indirect relationships with each other. Second, when some nodes' relationship changes, the entire network change must be considered. For example, (su (17, 1), su (1, 17)) = (+, −) indicates an "exploitation relationship." So Xuchang needs to indirectly obtain economic support from Wenshang. However, in the Sgn (D) matrix, (sd (17, 1), sd (1, 17) = (0, 0). This shows us that there is a "neutral relationship" between Xuchang and Wenshang, *i.e.*, there is no direct linkage transfer the two. (su (18, 4), su (4, 18) = (+, +) shows there is a mutualism between Zhoukou and Xiping, *i.e.*, they are mutually beneficial in development. However, in the Sgn (D) matrix, their

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38
1	0	+	+	-	-	+	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	-	0	+	-	-	+	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
3	-	-	0	-	-	-	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
4	+	+	+	0	-	+	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	+	+	+	+	0	+	-	+	+	+	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
6	-	+	+	-	-	0	-	-	-	-	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
7	+	+	+	+	+	+	0	+	+	+	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	+	+	+	+	-	+	-	0	+	+	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
9	+	+	+	+	-	+	-	-	0	+	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
10	+	+	+	+	-	+	-	-	-	0	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
11	-	+	-	-	-	-	-	-	-	-	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
12	+	+	+	+	+	+	+	+	+	+	+	0	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	+	+	+
13	+	+	+	+	+	+	+	+	+	+	+	-	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
14	+	+	+	+	+	+	+	+	+	+	+	-	+	0	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
15	+	+	+	+	+	+	+	+	+	+	+	-	+	+	0	+	+	-	+	+	-	+	-	+	+	-	+	+	+	-	+	+	-	+	-	-	+	+
16	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	0	-	-	+	+	-	+	-	+	-	-	+	+	+	-	+	+	-	-	-	-	+	+
17	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	+	0	-	+	+	-	+	-	+	-	-	+	+	+	-	+	+	-	-	-	-	+	+
18	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	0	+	+	-	+	+	+	+	+	+	+	+	-	+	+	+	+	+	-	+	+
19	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	0	+	-	+	-	+	-	-	+	+	+	-	+	-	-	-	-	-	+	-
20	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	-	0	-	+	-	+	-	-	-	+	+	-	-	-	-	-	-	-	+	-
21	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	+	+	+	0	+	+	+	+	+	+	+	+	-	+	+	+	+	+	-	+	+
22	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	-	-	-	0	-	-	-	-	-	-	+	-	-	-	-	-	-	-	+	-
23	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	-	+	+	-	+	0	+	+	+	+	+	+	-	+	+	-	+	+	-	+	+
24	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	-	-	-	+	-	0	-	-	-	+	+	-	-	-	-	-	-	-	+	-
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32	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	+	+	-	+	-	+	-	-	+	+	+	-	+	0	-	-	-	-	+	-
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34	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	+	+	-	+	+	-	+	-	+	-	-	+	+	+	-	+	+	-	0	-	-	+	+
35	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	-	+	+	-	+	-	+	+	-	+	+	+	-	+	+	-	+	0	-	+	+
36	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	-	+	+	+	+	+	0	+	+
37	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	-	-	-	-	-	-	-	-	-	-	+	-	-	-	-	-	-	-	0	-
38	+	+	+	+	+	+	+	+	+	+	+	-	+	+	-	-	-	-	+	+	-	+	-	+	-	-	+	+	+	-	+	+	-	-	-	-	+	0

Fig. 10. Direct economic connection matrix sgn(D).

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Fig. 11. Integral utility matrix sgn(U).

direct relationship reflects an "exploitation relationship": Zhoukou presents economic output to Xiping. In conclusion, in the entire network system of the Huaihe River, the economic relationships between cities and counties are not limited to one dimension; they can constitute two-dimensional networks and generate secondary relationship through the relationships between networks. Third, the utility function is no longer zero-sum. In the utility matrix Sgn (U), there are 463 positive and 685 negative values, which indicate that among the economic relationships of the Huaihe River, what they constitute is a comparatively competitive network. Based on Eq. (2), $J(F) = 463/685 = 0.676$ through the integral utility matrix Sgn (U). The economies of cities and counties are intertwined. Big cities' economies affect the counties', and each element exerts mutual influence on the others.

5.5. Pollution utility analysis

Similar to the economic utility analysis, through a flux matrix F, we established a direct flow matrix D (see Table 7A in Appendix and Fig. 12) and matrix Sgn(D) (see Fig. 13). The direct relationship between any two nodes can be compared across a diagonal line. Unlike economic relations, the direct pollution linkage between cancer villages and their adjacent cities is a mutually affected relationship, rather than a one-way impact of big cities on counties. For example, (sd(12, 1), sd(1, 12)) = (–, +) indicates an "exploited relationship," and (sd(22, 5), sd(5, 2)) = (+, –); (sd(6, 4) sd(4, 6)) = (0, 0) shows a "neutral relationship." In other words, Wenshang's pollution is affected by Jining and Luoshan's by Shenqiu, but there is no direct pollution interaction between Xiping and Luoshan. As shown in Table 4, as a source of pollution, Wenshang, Juye, Fugou, and Mengcheng transfer pollution to other counties and cities, reducing their own pollution degree. Different from direct economic relationships, direct pollution relationships show that cities can influence the cancer villages and *vice versa*. Also, through the analysis of the Sgn (D) matrix of cancer villages and their adjacent cities, we found that the known cancer villages are affected by the pollution output of adjacent cities (see Table 5). Likewise, the SD matrix has the same number of pluses and minuses because all of the nodes are either inputs or outputs of conservation (or 0). Based on Eq. (2), $J(F) = 640/730 = 0.877$ through the integral utility matrix Sgn (U).

Fig. 13 shows the integral utility matrix Sgn (U), in which the dark blue element is a "+" relationship, while light blue element is a "–" relationship. The results also show that there are some differences in matrix U. First, all of the elements in U matrix are non-zero, which shows that all nodes produce direct or indirect

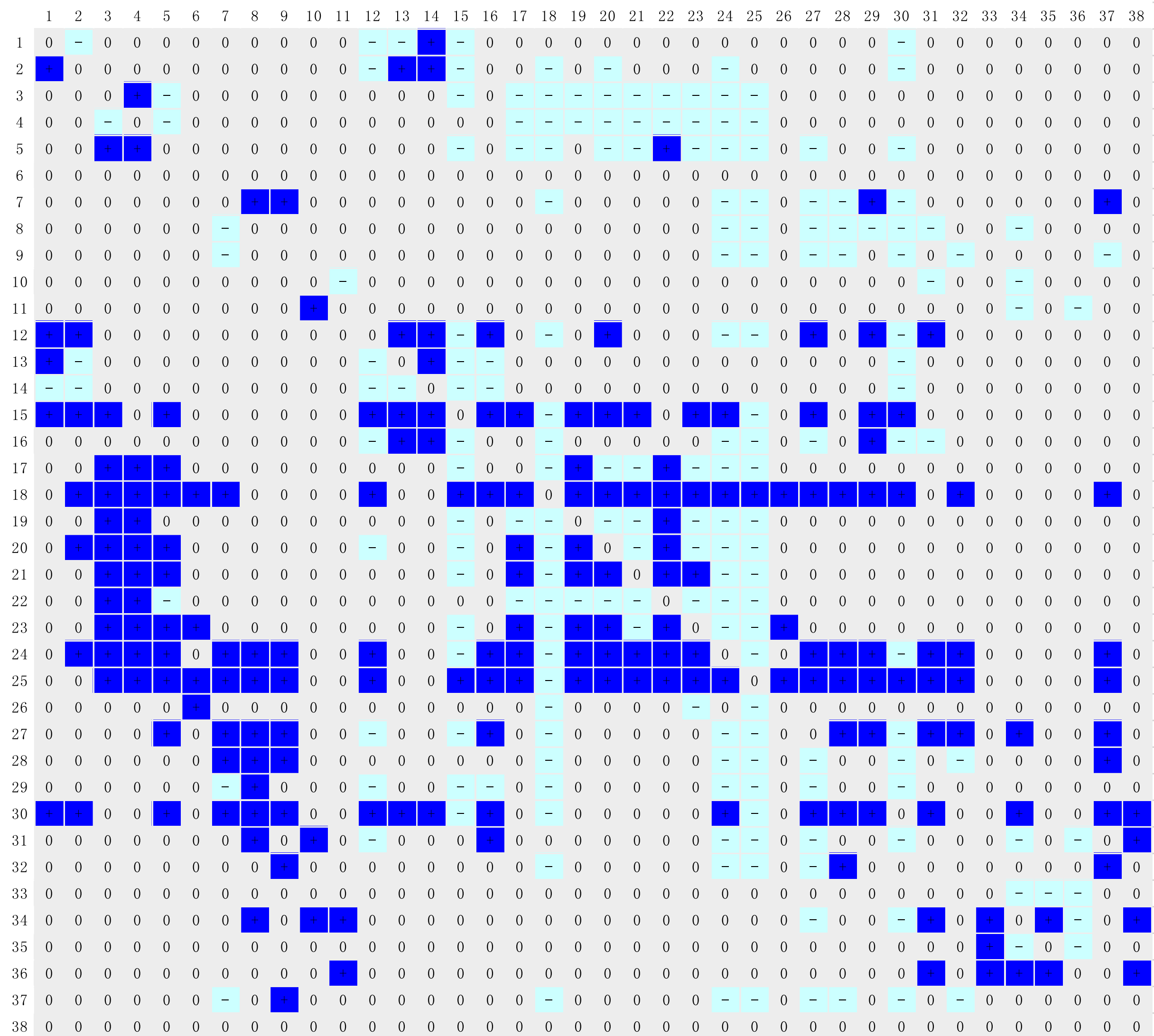

Fig. 12. Direct pollution connection matrix sgn(D).

relationships with one another. Second, when a node's relationship changes, the entire network change must be considered, as with the previous case about economic influence. For example, (su (22, 5), su (5, 22)) = (−, −) indicates a competitive relationship. Considering the indirect relationship between Luohe and Shenqiu, the two maintain a competitive relationship and are both affected by other cities' or counties' pollution. There is a competitive relationship in "receiving" pollution between Luohe and Shenqiu, which means if one city receives more pollution from outside, the other will receive less. It can be seen that big cities can influence cancer villages, while highly polluted counties like Shen Qiu can also affect big cities. Moreover, (su (18, 7), su (7, 18) = (+, +) shows that there is a mutualism between Zhoukou and Mengcheng; the pollution migration actually aggravates the pollution degree in both places taking indirect influence into accountant. Therefore, it is very likely that some industrial chains exist in both of these locations that connect the pollution emissions. Further, (sd (18, 7), sd (7, 18)) = (−, +) reflects that their direct relationship is an "exploitation relationship": Mengcheng absorbs pollutants from Zhoukou, decreases Zhoukou's pollution level. Mere concern for direct relationships will lead to ignorance of the source and convergence of pollution. Take Table 5 for example: the fact of cancer villages acting as the source of pollution increases when considering indirect pollution. Meanwhile, more cancer villages in turn become pollution impact providers, affecting additional cities and counties. Likewise, in Sgn (*D*), (sd(3, 1), sd(1,3)) = (0, 0) shows that there is no direct pollution relationship between Fugou and Wenshang, but in Sgn (*U*), (su(3, 1) su(1, 3)) = (+, −) indicates an indirect pollution relationship in which Fugou receives pollution from Wenshang. We found that seriously polluted cancer villages can increase pollution in adjacent cities and counties rather than act as mere "receivers" of pollution. Third, the utility function is no longer zero-sum. In the utility matrix Sgn (*U*), there are 640 positives and 730 negatives, indicating that from the point of view of pollution relationships along the Huaihe River, cancer villages and adjacent cities constitute a competitive network: the pollution in cities and counties are mutually influenced. Fourth, after considering the indirect relationships in the network, more "mutualistic" and "competitive" relationships appear (see Tables 6 and 7). Sixty-three (+, +) mutualism examples exist in indirect relationships, showing that both cities are seriously contaminated through transferring pollution to the other one. There are 98 pairs of (−, −) competitive relationships in which both cities decrease their pollutant concentration by transferring pollution to the other. Therefore,

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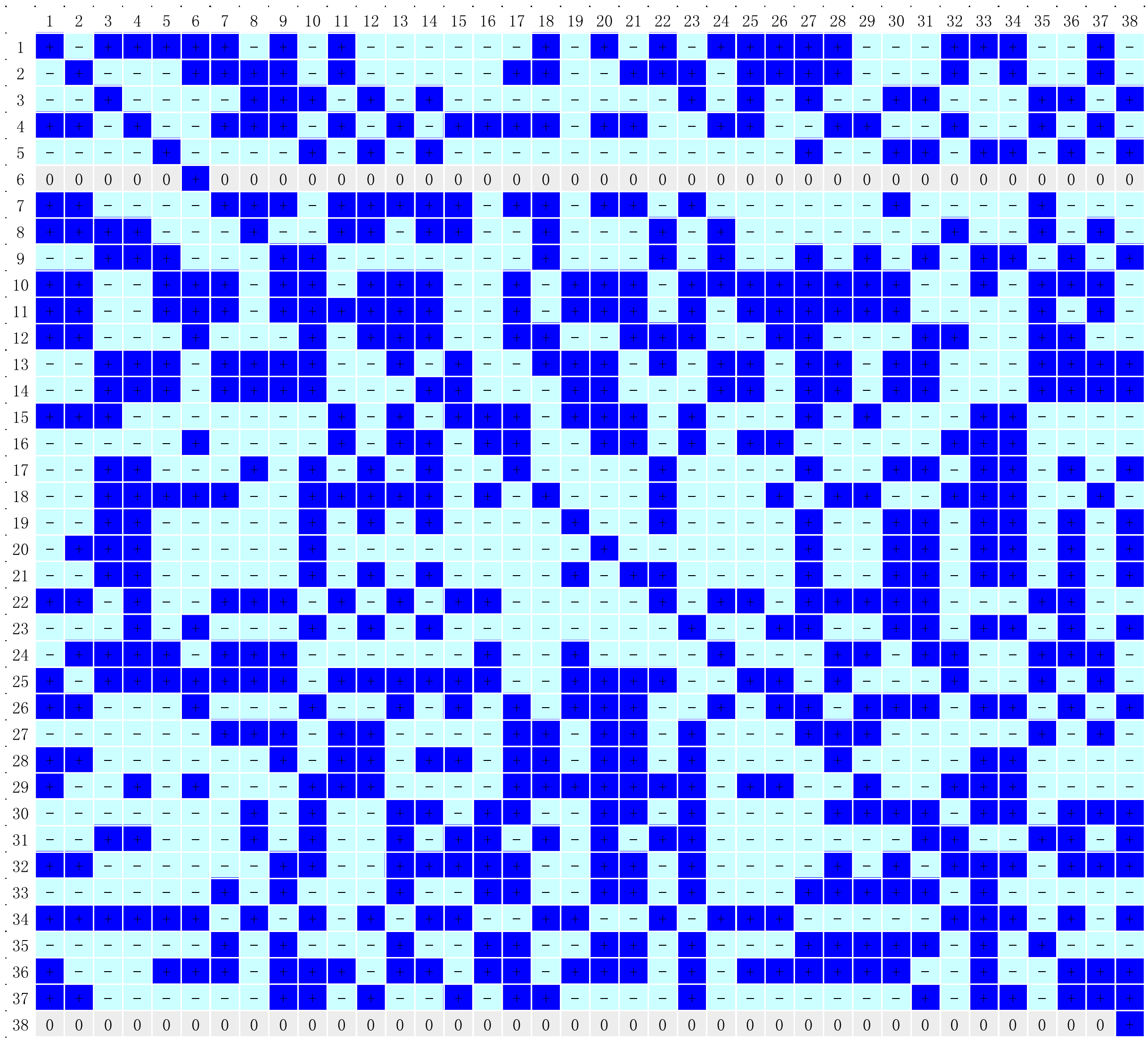

Fig. 13. Integral utility matrix sgn(U).

Table 4
Maximum, minimum, and average distance of pollution relationships in the "extremely strong" level.

Unit: km	Average distance of pollution relationships
Minimum	20.79
Maximum	58.63
Average	44.27

Table 5
The direct pollution interaction between cancer villages and big cities.

Cancer village	Source of pollution	Direct pollution interaction
Wenshang	Yanzhou	(+, −)
Juye	Qufu	(+, −)
Juye	Yanzhou	(+, −)
Fugou	Xiping	(+, −)
Mengcheng	Lingbi	(+, −)
Mengcheng	Shou	(+, −)
Mengcheng	Huaibei	(+, −)
Mengcheng	Huainan	(+, −)

for the 63 pairs of mutually affected cities and counties, they can invite trouble when transferring pollutants to other cities and counties (see Table 8).

Table 6
The list of cancer villages which are affected indirectly by surrounding cities.

Cancer village	Indirect pollution sources
Wenshang	Fugou, Shenqiu, Shou, Zhoukou, Kaifeng, Haozhou, Suzhou, Yangzhou
Juye	Shou, Xuchang, Zhoukou, Zhumadian, Fuyang, Suzhou
Fugou	Xuyi, Jining, Zhumadian, Suzhou, Xuzhou, Taizhou
Xiping	Mengcheng, Sheyang, Heze, Zaozhuang, Bengbu, Lu'an, Taizhou, Huainan
Shenqiu	Jining, Suzhou, Xuzhou, Suqian, Yangzhou, Huainan
Mengcheng	Lingbi, Shou, Jining, Heze, Xuchang, Kaifeng, Zhengzhou, Zhumadian, Xuzhou
Lingbi	Sheyang, Jining, Heze, Zhoukou, Lu'an, Taizhou, Huainan
Shou	Huaibei, Suqian, Huaian
Xuyi	Haozhou, Fuyang, Suzhou, Bengbu, Yangzhou, Taizhou
Sheyang	Jining, Qufu, Yunzhou, Xuchang, Pingdingshan, Kaifeng, Zhengzhou, Zhumadian, Haozhou, Xinyang, Xuzhou, Yangzhou, Taizhou, Huainan

Table 7
63 pairs of (+,+) mutualism examples exist in indirect relationships.

Cancer village	Indirect pollution sources
Wenshang	Xiping, Sheyang, Fuyang, Xinyang, Bengbu, Lu'an, Huaian, Huainan
Juye	Mengcheng, Lingbi, Sheyang, Luohe, Xinyang, Bengbu, Lu'an, Huainan
Fugou	Lingbi, Shou, Yunzhou, Fuyang, Suqian
Xiping	Wenshang, Lingbi, Shou, Qufu, Xuchang, Zhoukou, Kaifeng, Zhengzhou, Haozhou, Fuyang, Huaibei
Shenqiu	Yunzhou, Huaian, Yancheng
Mengcheng	Juye, Qufu, Yunzhou, Zhoukou, Taizhou
Lingbi	Juye, Fugou, Xiping, Yunzhou, Luohe, Haozhou
Shou	Fugou, Xiping, Luohe, Haozhou, Suzhou, Yangzhou, Yancheng
Xuyi	Jining, Qufu, Yunzhou, Xuchang, Pingdingshan, Kaifeng, Zhengzhou, Zhumadian, Xinyang, Huaibei, Xuzhou, Yancheng, Huainan
Sheyang	Wenshang, Juye, Fuyang, Suzhou, Bengbu, Huaibei

Table 8
98 pairs of (−,−) competitive relationships exist in indirect relationships.

Cancer village	Indirect pollution sources
Wenshang	Juye, Qufu, Yunzhou, Zaozhuang, Xuchang, Pingdingshan, Zhengzhou, Zhumadian, Xuzhou, Suqian, Taizhou
Juye	Wenshang, Fugou, Shenqiu, Qufu, Yunzhou, Zaozhuang, Pingdingshan, Huaibei, Xuzhou, Suqian, Yangzhou, Taizhou, Yancheng
Fugou	Juye, Xiping, Shenqiu, Mengcheng, Sheyang, Zaozhuang, Luohe, Xinyang, Bengbu, Huaibei, Lu'an, Yangzhou, Huainan
Xiping	Fugou, Shenqiu, Xuyi, Jining, Xinyang, Suzhou, Xuzhou, Yangzhou, Yancheng
Shenqiu	Juye, Fugou, Xiping, Mengcheng, Lingbi, Heze, Zaozhuang, Xuchang, Pingdingshan, Kaifeng, Zhengzhou, Luohe, Zhumadian, Xinyang, Bengbu, Huaibei, Lu'an, Taizhou, Huainan
Mengcheng	Fugou, Shenqiu, Zaozhuang, Pingdingshan, Xinyang, Bengbu, Huaibei, Xuqian, Lu'an, Huaian, Huainan
Lingbi	Shenqiu, Shou, Xuyi, Zaozhuang, Pingdingshan, Kaifeng, Zhengzhou, Zhumadian, Xinyang, Bengbu, Huaibei, Yangzhou, Yancheng
Shou	Lingbi, Jining, Heze, Zaozhuang, Xuchang, Pingdingshan, Kaifeng, Zhengzhou, Zhumadian, Xinyang, Xuzhou
Xuyi	Xiping, Lingbi, Heze, Zaozhuang, Luohe
Sheyang	Fugou, Haozhou, Suqian, Lu'an, Yangzhou, Huaian

6. Conclusions

Because of China's large population size, these Chinese data contribute significantly to the global burden of cancer [33]. Untangling the causal web linking urbanisation and human health needs a multidisciplinary approach, and metrics that capture the multidimensional process of urban-to-urban transformation show promise in the assessment of longitudinal changes in urbanicity and the subsequent health effects. The appearance of a cancer village is the result of the spatial-temporal distribution of human-land interactions, whose emergence manifests as an issue of human health and geography. The economic and pollution pathways are complex and defy simple solutions, but need to be rigorously investigated to understand and respond to the health effects, especially chronic disease, of urbanisation in Huaihe River Basin of China.

Based on the pollution utility relationship we found that "cancer villages" not only being affected by cities but also affect cities in the indirect relationships. We believe that "cancer villages" have a high incidence of malignant disease not just because of the pollution from its surrounding cities but may also due to the far-away city through the network. Further evidence of the pollution of water environment will adversely human health effects that may lead to the occurrence of gastrointestinal cancer from our research.

Policies to mitigate the adverse health effects of urbanisation need to meet the health-care needs of highly vulnerable populations, and must follow up these populations as they potentially transfer health-care burdens to cancer villages. The next decade of urbanisation in China will demand innovative health policies that address the needs of residents living in big cities while providing health services for people who remain in surrounding small urban areas or villages in river basin.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.apenergy.2016.06.132.

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