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Urban drought vulnerability assessment – A framework to integrate socio-economic, physical, and policy index in a vulnerability contribution analysis

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ABSTRACT

The frequent occurrence of drought seriously hinders urban sustainable development. Decreasing urban drought and reducing drought risk entails a good understanding of urban drought vulnerability (UDV). Based on physical, socio-economic, and political indicators, this study evaluated and analyzed the urban drought vulnerability in the Beijing-Tianjin-Hebei (BTH) region from the following aspects: spatio-temporal analysis and contribution analysis. Results indicated that (1) the UDV of 13 cities kept increasing from 1990 to 2016. By 2016, 13 cities were highly vulnerable; (2) social and economic factors were considered as the main factors contributing to high drought vulnerability; and (3) public budget expenditure, GDP, and indicators related to education significantly contributed to UDV. This study provides a theoretical basis for the government to manage drought.

1. Introduction

Cities, as the shelter of more than half of the world's population, undertake the function of socio-economic activities, social development and administrative work (UN-Habitat, 2011). Inevitably, the dense population and rapid urbanization is increasing the risk to disasters caused by climate change (Tapia et al., 2017).

In particular, drought is a major natural global hazard which can be costlier than those from any other natural hazard (Ahmadalipour, Moradkhani, Castelletti, & Magliocca, 2019; Marcos-Garcia, Lopez-Nicolas, & Pulido-Velazquez, 2017; Oikonomou, Tsesmelis, Waskom, Grigg, & Karavitis, 2019). Global economic losses caused by droughts are estimated at US$ 6–8 billion per year, which is significantly more than that from other meteorological disasters (Smith & Katz, 2013). The occurrence of drought breaks the balance between urban water demand and supply which has significantly increased the vulnerability of urban systems (Nazemi & Madani, 2018). Persistent droughts can lead to a significant depletion of reservoirs' storages and groundwater levels, with a subsequent broad range of socio-economic and environmental impacts (Zhang, Sun, Li, Xiao, & Singh, 2015). Climate change is expected to aggravate this trend, causing greater risks to the society, the environment, and the sectors which depend on precipitation and water resources (IPCC, 2014). Nazemi and Madani (2018) proposed that new insights, tools and methodologies are needed for better representation of complex interactions within coupled human and water systems in urban regions.

A comprehensive understanding of drought vulnerability can not only reduce drought vulnerability, but also is an important part of effectively reducing the negative impact of drought and urban risk (Kim, Jain, Lee, Chen, & Park, 2019; Zarafshani et al., 2012). According to the IPCC, vulnerability is the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes (IPCC, 2014). Many scholars have been conceptualizing drought vulnerability differently based on the objectives to be achieved and the methodologies employed (Chang, Yip, Conger, Oulahen, & Marteleira, 2018; Fatemi, Ardalan, Aguirre, Mansouri, & Mohammadfam, 2017; Kita, 2017). Particularly, agricultural drought vulnerability has been widely discussed, including aspects related to the selection of drought indicators and vulnerability assessment system (Etienne, Devineni, Khanbilvardi, & Lall, 2016; Shen et al., 2019). However, it is especially concerning that few studies of drought vulnerability focus on the urban level.

Even if the study content is the same, based on drought, different study objects apply different study systems and the applicability of the results is different. Due to the difference of main subject of economic activities, the index system of agricultural drought vulnerability may not be suitable for the study of urban scale. Further, the study of agricultural drought vulnerability has less reference value to urban

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planning and construction managers. On the contrary, studies of drought vulnerability focused on the urban scale will explicitly provide the decision-makers with the theoretical basis to mitigate urban drought and decrease urban drought vulnerability.

Understanding the concept of vulnerability and extensive literatures, we define urban drought vulnerability as the extent to which the balance of urban water demand and supply is disrupted by drought and the city is unable to cope with. Cities are not simple objects to analyse. Urban system is characterized by a series of interactions between sub-systems, including infrastructure sub-systems, social sub-systems, economic sub-systems, etc. (Feliu et al., 2017). While exposure boosts the probability of a hazard, the society's overall vulnerability to a disastrous outcome is independent of exposure and begins with the economic, political, and social structures and ideologies that shape the distribution of human, physical, political, and social capital in a society (Ward & Shively, 2017). Based on urban characteristics, we emphasize the importance of socio-economic factors (including water infrastructure, etc.) to drought vulnerability of urban system, as distinct from the agricultural scale. The level of risk that the hazard poses to people is directly related to socio-economic factors. Meanwhile, increased losses from droughts are increasingly being focused on societal vulnerability (Ward & Shively, 2017; Zarafshani et al., 2012).

The overall objective of this study was to assess and analyze the urban drought vulnerability (UDV) of the Beijing-Tianjin-Hebei (BTH) region, using the framework that integrates socio-economic, physical, and policy index. For that, we estimated the UDV of 13 cities from 1990 to 2016, based on the entropy method. Accordingly, ArcGIS was used for the spatio-temporal analysis of drought vulnerability. After that, the contribution analysis of three parameters and ten indicators was individually performed. Based on this analysis, we established specific methods to decrease UDV. Through this study, we answered the following questions: (1) What is the degree of UDV in the BTH region?, (2) What are the spatial and temporal characteristics of the BTH region?, (3) What are the influential factors of UDV in the BTH region?, and (4) How to relieve a drought disaster and decrease UDV?

2. Literature review

2.1. Urban drought versus water scarcity

There are four types of drought: meteorological drought, hydrological drought, agricultural drought, and socio-economic drought. Cities are a system composed of various activities of humanity. The negative impact of urban drought is mostly reflected in socio-economic aspects. Therefore, urban drought mainly comes into the category of socio-economic drought.

The term “urban drought” and “water scarcity” both imply an imbalance between water supply and demand. However, there are several important distinctions between them. Based on the extensive studies (Berbel & Esteban, 2019; Zhang, Chen et al., 2019), the scope of application and content are distinguishing. The former places specific focus on urban area whereas the later one can be used to describe all manner of water shortages in all geographic locations. And urban drought is used to describe a temporary other than long-term water stress. Besides, urban drought itself can be a main cause of water scarcity, while water scarcity mainly describes the imbalance state. A legible understanding of urban drought will provide a specific direction for studies.

2.2. Drought disasters

Drought is a serious natural disaster characterized by water deficit, which affects the lives of residents and the production of enterprises and then hinders the urban economic development. It has aroused wide attention and discussion with severely affecting urban and social sustainable development (Yang, Xia, Zhang, Zhan, & Qiao, 2018). Studies on drought can provide scientific and accurate basis for decision-makers to develop reliable drought-prevention and drought-resistant strategies.

In recent years, studies on drought disaster have changed from passive response to active prevention. It is crucial for the detection and prediction of drought to minimize the effects of drought. Studies related to drought have gradually changed from the single impact study (van Vliet & Zwolsman, 2008) to the prediction (Hao, Hao, Singh, Ouyang, & Cheng, 2017; Hunt & No, 1991), monitoring (West, Quinn, & Horswell, 2019; Zhang, Chen, Li, Chen, & Niyogi, 2017), the exploration of causes (Gebremeskel et al., 2019) and the vulnerability of drought (Liu, Guo et al., 2019; Wang, Yang, Chang, & Zhang, 2019; Wu, Zhou, Zhang, Jin, & Zhou, 2019). Further, among lots of indexes, the standardized precipitation index (SPI) and the standardized precipitation evapotranspiration index (SPEI) are widely used to predict and assess the drought disaster (Parsons, Rey, Tanguy, & Holman, 2019). Based on the indexes, many studies have created new indicators and methods (liu, Zhang et al., 2019). Wang, Yu et al. (2019) developed a multi-scalar drought index, the standardized precipitation evapotranspiration runoff index (SPERI) based on the principles underlying the calculation of SPI and SPEI. More recently, Remote sensing technology opens the door for drought monitoring (Jiao, Wang, Novick, & Chang, 2019). West et al. (2019) charted the rise of remote sensing for drought monitoring, examining key milestones and technologies for assessing meteorological, agricultural and hydrological drought events. And then they reflected on challenges the research community has faced to date, looked ahead to the future in terms of new technologies, analytical platforms and approaches.

2.3. Vulnerability versus risk

Risks arise from the interaction between hazard, vulnerability and exposure. Multitude of studies have investigated the impacts (Ahmadalipour et al., 2019), management (Chang et al., 2018; Kita, 2017; Liu, Guo et al., 2019) of drought risk in various parts of the globe. It has been concluded that climate change caused by various factors will exacerbate drought in many parts of the world (Liu, Guo et al., 2019; Tapia et al., 2017).Current studies have emphasized the transition from "crisis management" to "risk management" for disasters mitigation.

Vulnerability is an important component of risk. Reducing vulnerability is efficient strategies for reducing and managing the risks of climate change contribute to sustainable development. Many literatures have applaud that natural hazards are almost purely exogenous, and with global climate change possibly augmenting these pressures, perhaps the only viable strategy for disaster risk reduction is to enhance the factors that decrease societal vulnerability (Zarafshani et al., 2012).Vulnerability is influenced by a wide range of social, economic and cultural factors and processes that has been incompletely considered to date. Therefore, it is important to investigate the changes of vulnerability with detail and understand its impacts on drought risk reduction.

2.4. Urban drought vulnerability

The concept of vulnerability has been applied in various aspects (Mosoarca et al., 2019; Soon, Krzyzaniak, Shuttlewood, Smith, & Jack, 2019), studies on disaster vulnerability have been widely discussed (Abebe, Kabir, & Tesfamariam, 2018; Nguyen, Liou, & Terry, 2019). The assessment of vulnerability provides a new perspective for the exploration of influencing factors and the decrease of system risk.

Many drought vulnerability studies have been done at agriculture aspects, with extensive discussions on framework building (Shen et al., 2019), methodology (Kamali, Abbaspour, Wehrli, & Yang, 2018), and index selection (Hazbavi, Baartman, Nunes, Keesstra, & Sadeghi, 2018). Wilhelmi and Wilhite (2002) created a framework for derivation of an agricultural drought vulnerability map through development of a numerical weighting scheme to evaluate the drought potential of the classes within each factor. Zhang et al. (2015) analyzed the agricultural vulnerability based on precipitation, as well as socioeconomic and physical indicators. In addition, studies done on national or regional scales are also widely discussed (Ahmadalipour & Moradkhani, 2018; Hannaford, 2018; Niu, Kang, Zhang, & Fu, 2019). Ahmadalipour and Moradkhani (2018) carried a multi-dimensional modeling framework out to investigate drought vulnerability at a national level across the African continent. Hannaford (2018) made extensive use of the historical written record to analyse the comparative root-causes of the vulnerability and resilience in the area between the Zambezi and Save rivers in southern Africa. The selection of indicators was also widely discussed. Various drought indexes have been developed to estimate drought vulnerability. Indicators related to agriculture such as terrain, crop diversity, non-agricultural share of GDP and grain yield are applicable to agricultural drought vulnerability, which have been widely used. Li et al. (2016) selected grain yield variability, non-agricultural share of GDP, ratio of irrigation area to assess the agricultural vulnerability of 243 rural counties on the Chinese Loess Plateau. Economic, social and infrastructure indicators have been widely used in national or regional drought vulnerability. Ahmadalipour and Moradkhani (2018) selected indicators from land use, economy, health, infrastructure, social and water resources dimensions to assess drought vulnerability.

Studies about agricultural drought vulnerability have less reference significance for urban sustainable development, while studies focused on national or regional are defective in providing the proposals of specific and accurate management. In contrast, studies conducted at the urban level tend to be more specific. However, only a few studies have addressed the urban drought vulnerability and the selection of indexes. Nazemi and Madani (2018) emphasized the impact of significant growth in population and anthropogenic activities on the vulnerability of human systems to changes in water quantity and/or quality. They provided a brief overview on the water-related threats to human society and the context of water security. Finally, they called for the studies of new technologies and effective multichannel mechanisms of water system. Kim, Park, Yoo, and Kim (2015) proposed Drought Hazard Index (DHI) and Drought Vulnerability Index (DVI) to map the drought risk for 229 administrative districts across South Korea. They determined seven indicators such as irrigated land, agricultural occupation, crop production, population density (PD), municipal Water (MW), industrial Water (IW), and agricultural water (AW). Although many studies provide references for index selection (Li et al., 2016), studies on urban scale need more accurate and appropriate indicators. As human being's economic and social activities are the main subject of cities, anthropogenic factors are essential for urban drought vulnerability. Anthropogenic factors are the primary drivers of induced environmental degradation (Chen & Sun, 2017; Mahmoud & Gan, 2018).

Overall, the assessment of vulnerability focused on urban drought is essential for decision makers to improve the urban drought plan, which improves sustainability of urban. Therefore, this study was to explore the influencing factors of urban drought vulnerability. Section 3 is study area, which has a comprehensive description of BTH regions. What followed is Section 4 focusing the study method. Results and discussions are presented in Section 5, followed by conclusions in Section 6.

3. Study area

The BTH region (36°01′ N − 42°37′N, 113°04′ E − 119°53′E, Fig. 1) is formed by two municipalities, Beijing and Tianjin, and 11 cities of the Hebei Province, namely Baoding, Langfang, Tangshan, Handan, Xingtai, Qinhuangdao, Cangzhou, Hengshui, Chengde, Zhangjiakou, and Shijiazhuang (Zhao et al., 2018). Typically, the BTH region has a warm temperate continental monsoon climate with hot and rainy summers and cold and dry winters. This region has an area of 218,000 m^2 and a population of 110 million people. Moreover, its Gross Domestic Product (GDP) reached US$1.06 trillion in 2016, accounting for 9.25 % of the country's GDP. The BTH region is the core of China's economic and social development.

As a driving force for China's development, the BTH region is facing severe urban drought and water shortage (Sun, Pan, Gu, Lu, & Wang, 2018). The annual average precipitation in the region is 528 mm. The average water resource per capita is 218 m^3, which is only a ninth of the national average. Since 1990, the BTH region has been suffering from droughts, some of which occurred with large degree and wide coverage (1992, 1993, 1997, 2000 and 2014). What' more, given the growing water demand largely induced by economic growth and population expansion, water resources in the BTH city region have been excessively exploited. The utilization degree of shallow groundwater is 130 %, and the amount of water entering the sea declined from 240 billion m^3 in the 1950s to 40 billion m^3. Under the combination of climate change and human activities, the total annual water resources declined from 291 billion m^3 in 1956–1979 to 166 billion m^3 in 2001-2010.

The government has realized that the water issue is the foremost problem for the sustainable and coordinated development of the BTH region. The total number of environmental regulatory policies in Beijing, Tianjin and Hebei are 163, 99, and 284, respectively during 2003–2014 (Zhang, Zhang, Zhang, & Li, 2019). And the BTH region has implemented an integrated water resource allocation pattern under the strategy of “The outline for the coordinated development of Beijing, Tianjin and Hebei”. Specifically, in response to the drought, the government has also introduced relevant policies. The drought management policies of 13 cities issued by the governments focused on the prevention and rescue of meteorological disasters, water demand (GDP, education, water price and tax) and reservoir management. Due to the limited number of policies promulgated prior 2008 and city data, this paper only collected drought and water resource management polices of Beijing, Tianjin and Heibei province from 2009 to 2016. During these 8 years, the total number of drought regulatory policies in Beijing, Tianjin and Hebei are 1201, 81, and 355, respectively. Combination with city characteristics, 13 cities all enacted Natural Disaster Relief Ordinance, Pilot Implementation Plan for Water Resource Tax Reform, etc. However, different UDV implied the differences in policy implementation and refinement (socio-economic, infrastructure, etc.). Beijing intensified drought management regulations compared to other cities, as evidenced by district-county drought management policies explicitly. On the contrary, urban drought vulnerability of Tianjin was high owing to few policies.

Given the core status and severe drought, it is necessary to conduct a city level analysis on drought vulnerability of the BTH region.

4. Data and methodology

4.1. Urban drought vulnerability model

The study framework of this study is shown in Fig. 2.

The positive or negative effects of anthropogenic factors on vulnerability are widely recognized. Vulnerability is the result of diverse historical, social, economic, political, institutional, and environmental conditions and processes (Oppenheimer et al., 2012; Zhang et al., 2015). Population, economy, and water infrastructure are dominant factors for index selection to assess drought vulnerability (Yuan et al., 2015). Comprehensive consideration of the concept of vulnerability, urban scale and regionalism of BTH regions, we developed 10 indicators from three categories of physical, socio-economic, and political parameters referred to relevant literatures about agricultural drought vulnerability (Stefano et al., 2015), climate change vulnerability (Sarkodie & Strezov, 2019; Tapia et al., 2017) and urban water shortage (Boruff, Biggs, Pauli, Callow, & Clifton, 2018; Koutroulis et al., 2019; Srinivasan, Seto, Emerson, & Gorelick, 2013). The details of the indicators are shown in Table 1.

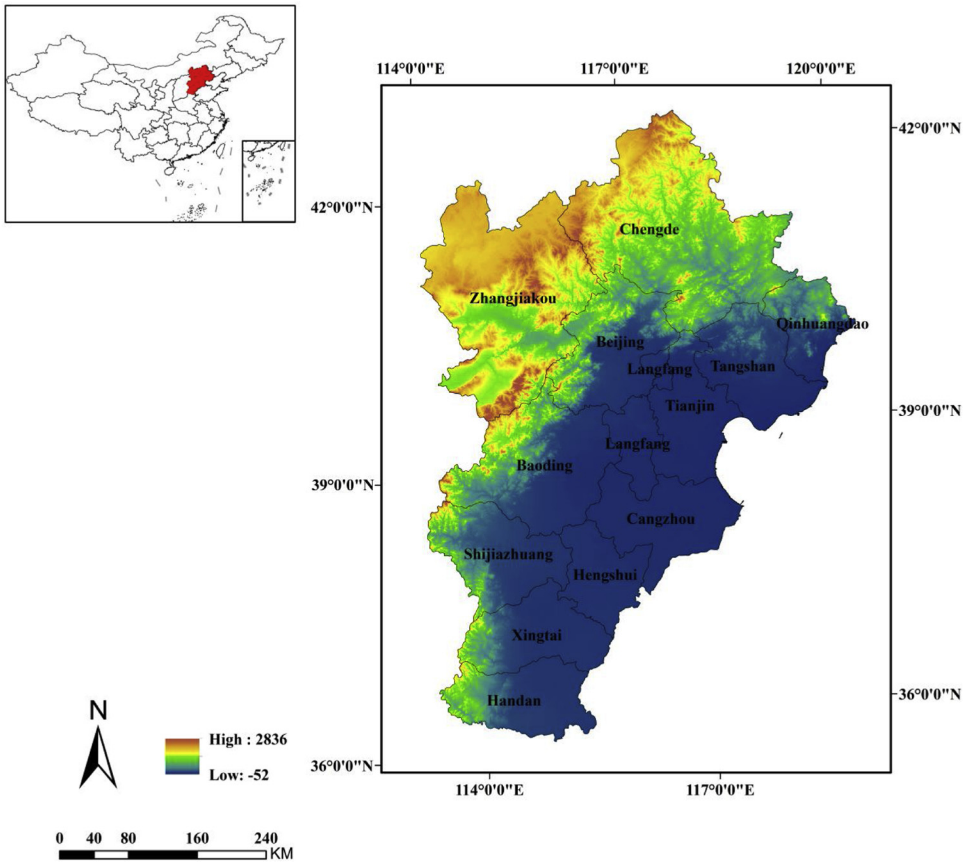

Fig. 1. Hypsometric map of the Beijing-Tianjin-Hebei (BTH) region.

4.2. Calculation of urban drought vulnerability

4.2.1. Standardized drought indexes

The indicators must be standardized to make the data comparable and eliminate the effect of dimension. Indicators are divided into positive and negative indexes, depending on the difference of the evaluation effect.

Positive and negative indexes are standardized using the following equations, respectively:

$$x'_{ij} = \frac{x_j - x_{min}}{x_{max} - x_{min}} \quad (1)$$

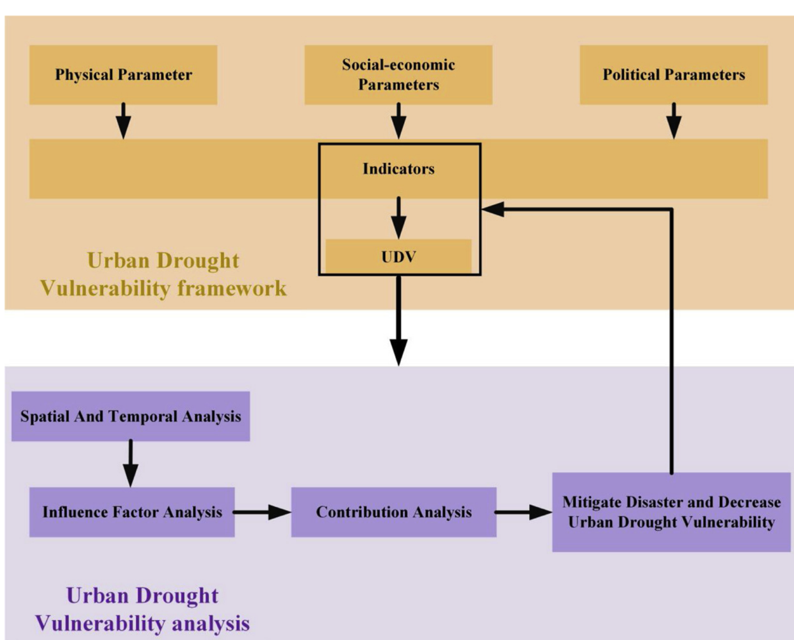

Fig. 2. Overall study scheme.

Table 1
Indicators of urban drought vulnerability.

Indicator	Category	Source	Relevance
Length of Water Supply Pipelines (km)	physical parameters	Beijing Municipal Bureau of Statistics, 2005-2017Beijing Municipal Bureau of Statistics, -, 2017Beijing Municipal Bureau of Statistics, 2005-2017, Tianjin Statistical Yearbook 2004-2017Tianjin Municipal Bureau of Statistics, -, 2017Tianjin Statistical Yearbook 2004-2017, Hebei Economic Yearbook 1991-2017Hebei Provincial Bureau of Statistics, -, 2017Hebei Economic Yearbook 1991-2017, City Statistical Yearbook 1991-2017National Bureau of Statistics China, -, 2017City Statistical Yearbook 1991-2017.	(Boruff et al., 2018)
Coverage Rate of Afforestation in Developed Area (%)	physical parameters		(Srinivasan et al., 2013)
Number of Beds in Health Care Institutions	physical parameters		(Sarkodie & Strezov, 2019)
Production Capacity of Urban Tap Water ($10^4 m^3$/ day)	physical parameters		(Stefano et al., 2015; Boruff et al., 2018)
Built-up Area (km^2)	physical parameters		(Srinivasan et al., 2013)
Population Density (person/km^2)	socio-economic parameters		(Stefano et al., 2015; Busby, Smith, Krishnan, Wight, & Vallejo-Gutierrez, 2018)
Per Capita Disposable Income (yuan)	socio-economic parameters		(Srinivasan et al., 2013; Wang, Yu et al., 2019; Wang, Yang et al., 2019)
Number of Students Enrolled in Regular Institutions of Higher Education	socio-economic parameters		(Busby et al., 2018; Koutroulis et al., 2019)
Gross Domestic Product (10^8yuan)	socio-economic parameters		(Koutroulis et al., 2019; Wang, Yu et al., 2019; Wang, Yang et al., 2019)
Public Budget Expenditure (10^8yuan)	political parameters		New indicator

Table 2
Urban drought vulnerability scores.

Vulnerability score	Vulnerability level
0.00-0.16	no or least vulnerability
0.16-0.33	low vulnerability
0.33-0.67	medium vulnerability
0.67-0.83	high vulnerability
0.83-1	extreme vulnerability

$$x_{ij}^{'} = \frac{x_{max} - x_j}{x_{max} - x_{min}} \tag{2}$$

where $x_{ij}^{'}$ = standardized value; x_j = value of indicator j; x_{max} = maximum value of indictor j; and x_{min} = minimum value of indicator j.

4.2.2. Weighting procedure

The weight of indicators can be divided into objective and subjective weighting. Subjective weighting depends on subjective factors, and the amount of qualitative data is larger than that of quantitative data. The entropy method is an objective weighting method, which can reflect the utility value of the index. Its weight value has higher credibility and accuracy than that of the subjective weighting method. Therefore, the entropy method was applied to calculate the weight index.

The proportion of the year index value in comparison with all the indexes was calculated using the following equation:

$$y_{ij} = \frac{x_{ij}^{'}}{\sum_{i=1}^{m} x_{ij}^{'}} (0 \le y_{ij} \le 1) \tag{3}$$

where y_{ij} = the proportion of the index value of year i in the index of item j; m = the total number of years.

The entropy value was calculated using the following equation:

$$e_j = -K\sum_{i=1}^{m} y_{ij} \ln y_{ij} (K = \frac{1}{\ln m}) \tag{4}$$

where e_j = the information entropy value of index j.

The weighting was performed using the following equations:

$$d_j = 1 - e_j \tag{5}$$

$$w_j = \frac{d_j}{\sum_{i=1}^{m} d_j} \tag{6}$$

where d_j = the information utility value of index j; w_j = the weighting of index j.

4.2.3. Urban drought vulnerability score

The vulnerability score was calculated using the following equation:

$$UDV = \sum_{i=1}^{n} y_{ij} w_j \tag{7}$$

The vulnerability were classified into five levels according to the drought vulnerability assessment model (Table 2), which is based on extensive literature (Oikonomou et al., 2019).

5. Results and discussion

Until 2016, the BTH region was vulnerable to severe drought (Table 3). Seven cities, namely Tianjin, Shijiazhuang, Tangshan, Handan, Chengde, Zhangjiakou, and Cangzhou, were extremely vulnerable to urban drought. The remaining six cities, such as Beijing, were highly vulnerable. Tianjin had the highest UDV (0.925), which is consistent with its rapid economic growth and population expansion. Langfang has the lowest UDV (0.729). Recognizing the spatio-temporal characteristic of UDV is the basis of reducing vulnerability and risk. Contribution analysis contributed to our exploration of UDV reduction.

5.1. Spatial and temporal analysis

5.1.1. Temporal variation of drought vulnerability of 13 cities

The trends of 13 cities from 1990 to 2016 are shown in Fig. 3 and the growth rate of vulnerability in each year relative to the previous year is calculated in Fig. 4. UDV showed a clear upward trend in generally of 13 cities (Fig. 3). Fig. 4 provided a detailed explanation of this

Table 3
Urban drought vulnerability (UDV) of 13 cities in 2016.

Cities	Scoring	Cities	Scoring
Tianjin	0.925	Xingtai	0.817
Shijiazhuang	0.896	Beijing	0.809
Tangshan	0.887	Qinhuangdao	0.794
Chengde	0.882	Baoding	0.769
Cangzhou	0.856	Hengshui	0.758
Zhangjiakou	0.853	Langfang	0.729
Handan	0.834		

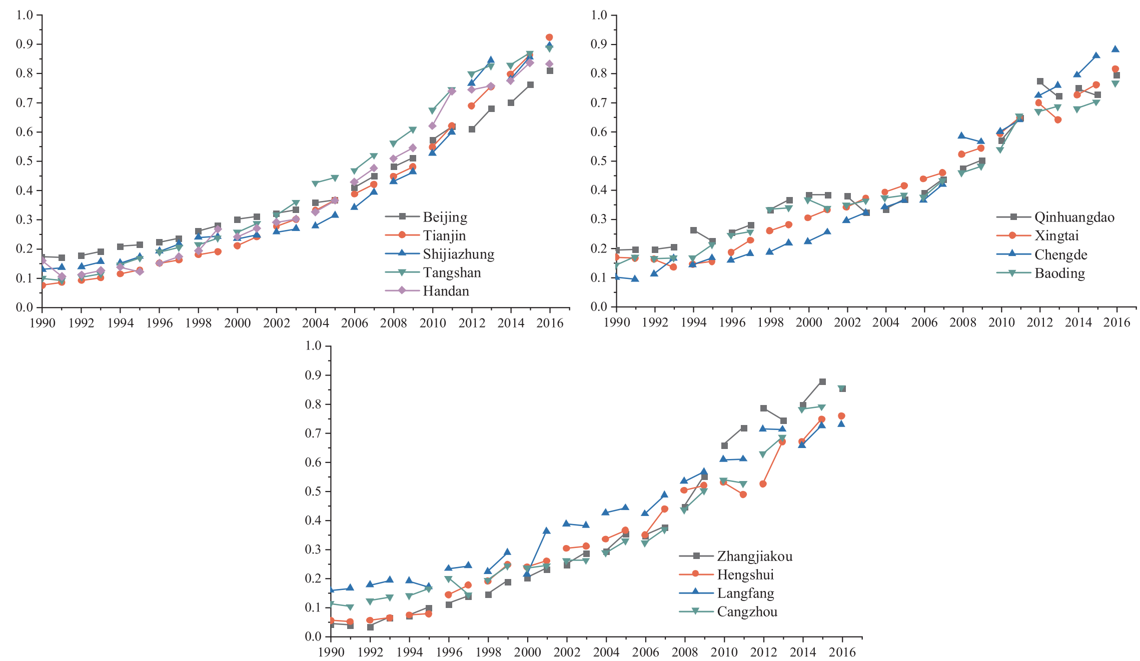

Fig. 3. Drought vulnerability trend graph for 13 cities from 1990 to 2016.

trend. For Beijing, Tianjin, Shijiazhuang, and Tangshan, the trend of vulnerability remained at a relatively stable level. The amplitude of the fluctuations is in the larger trend for the remaining cities. In Langfang, UDV declined in 1994, 1995, 1998, 2000, 2003, 2006, 2013, and 2014. The UDV of Handan sharply decreased in 1991, with a decline of approximately 51.4 %. Handan presented a downward trend in 1995, 2000, and 2016. The results reflected the instability characteristics of UDV, representing a significant challenge to decision makers.

5.1.2. Spatial distribution of drought vulnerability in the BTH region

The growth rate maps (left) and spatial distribution maps (right) of UDV at five-year intervals of the BTH region were established (Fig. 5). From 1990–1996, Zhangjiakou and Hengshui had the largest growth rates. From 1996–2001, the growth rates of Zhangjiakou and the southern region were the largest. From 2001–2006, the northern region had an overall large growth rate. From 2006–2010, Zhangjiakou had the highest growth rate. From 2010–2016, Cangzhou had the highest growth rate. From the growth rate maps, we can observe that that the growth rate of the central region of BTH is low, while the surrounding areas have a high growth rate. This is also the process of transferring the high vulnerability from the central part (Beijing, Langfang, and Baoding) in 1996 to the surrounding cities in 2016.We observed the characteristic that UDV from the central region spread and transferred to its surroundings.

5.2. Contribution analysis

5.2.1. Contribution analysis of three parameters

Based on understanding the UDV of the BTH regions, we calculated the contribution percentage of physical, socio-economic, and political parameters to the UDV of each city. The results are shown in Fig. 6.

For all cities, physical and socio-economic parameters were the main cause for UDV in the BTH region. Two parameters accounted for nearly 80 % of the UDV in most cities. The socio-economic parameters proportion of UDV exceeded physical parameters during the period of 2002–2006 for ten cities (Fig. 7). It is believed that the result of the rapid economic development and growth that started in 2000, which led to an increased water demand. From 2000, China has achieved high rates of total factor productivity (TFP) growth relative to the United States. High TFP growth rates are always a major factor behind China's rapid economic growth rate (Cooper, 2014). Meanwhile, incomplete infrastructure and uncontrolled urban expansion are considered the main reasons for the large proportion physical parameters of UDV.

In ten cities, including Beijing and Tianjin, socio-economic

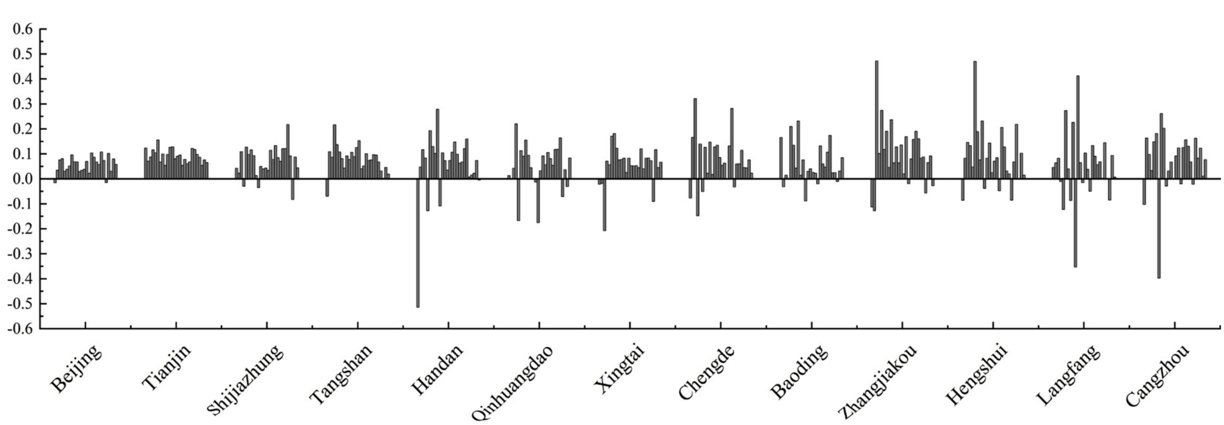

Fig. 4. UDV growth rate of 13 cities.from 1990 to 2016.

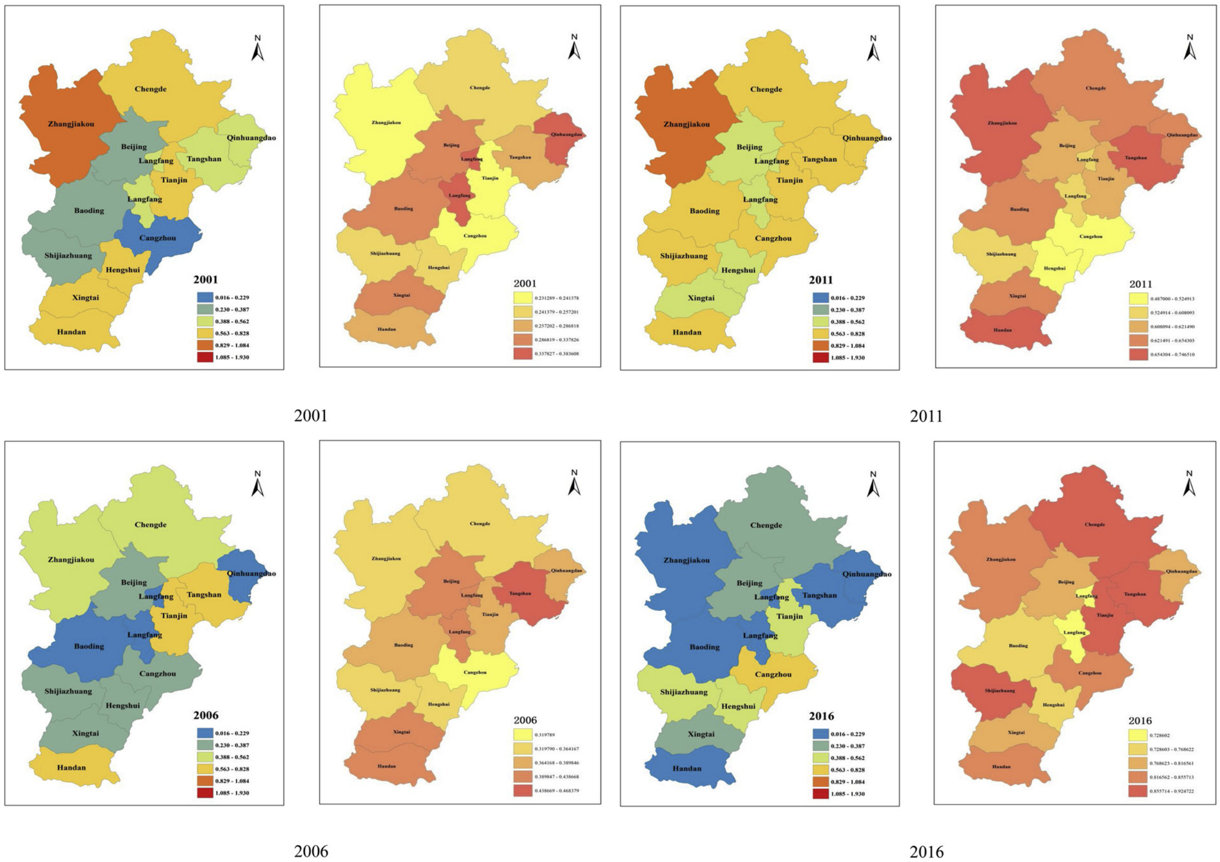

Fig. 5. UDV growth rate (left) and spatial distribution maps (right) of the BTH region.

parameters contribute the most to UDV. They have developed with population expansion and rapid economic growth, both of which caused enormous water demand. The contribution of socio-economic parameters in Qinhuangdao is the largest. Zhangjiakou's socio-economic contribution to UDV accounts for 37.2 %, which is the smallest among the 13 cities. This is caused by Zhangjiakou's heavy responsibility of ecological and environmental protection to Beijing. Conversely, the physical parameters of three cities (Zhangjiakou, Hengshui, and Langfang) contribute most to UDV. This suggests that the water infrastructures in these three cities are incomplete. For physical parameters proportion of UDV, Zhangjiakou was the highest and Qinhuangdao was the smallest.

5.2.2. *Contribution analysis of ten indicators*

The contribution of indicators to UDV for each city is illustrated in Fig. 8. Because there are several indicators, this study analyzed the top three indicators of 13 cities for index contribution analysis. The top three indicators for each city are similar but different in detail. For all cities, public budget expenditure contributed the most to UDV. In Tianjin and Chengde, GDP and length of water supply pipelines are the second and third largest contributors, respectively. Similarly, the second and third largest contributors in Shijiazhuang and Zhangjiakou are length of water supply pipelines and GDP. Clearer information for each city is shown in Fig. 9.

5.2.2.1. Public budget expenditure. Public budget expenditure was a critical factor, which contributed the most to UDV in all cities. In eight cities, the proportion of public budget expenditure to UDV was higher than 20 %. The contribution of public budget expenditure in Cangzhou was the largest, at 23.0 %. Zhangjiakou's public budget expenditure contributed to UDV was the smallest (17.9 %) owing to the more than 666.7 km^2 afforested area. The government is more likely to consider the ecological environment of Zhangjiakou in comparison with other areas, because of its function as an ecological barrier for Beijing. Similarly, the BTH region, as the capital economic circle, has also been supported by the government. However, the contribution of public budget expenditure to UDV has increased, not decreased. This implied that the government was limited in pertinence and accuracy. According to China statistical methods and dimensions, public budget expenditure includes general public service, education, science, technology, culture, sports, media, social security, employment, healthcare, transportation, and so on. Therefore, the government expenditure is significantly correlated to socio-economic development and infrastructure, which is also related to the adaptive capacity of cities during a drought disaster. However, there is little expenditure directly related to urban drought disasters, such as that involving urban water supply systems and green irrigation. Without a coordinated, national drought policy, nations will respond to drought in a reactive, crisis management mode, which are known to be untimely, poorly coordinated, and inefficient (Sivakumar et al., 2014).

5.2.2.2. Gross domestic product. Rapid economic development can cause environmental damage and increased water demand. It can be seen from the contribution index that in 11 cities (all except Xingtai and Hengshui) GDP is one of the first three indicators. Tianjin presents the largest share (16.0 %), followed by Chengde (15.1 %), Tangshan (14.9 %), and Langfang (14.6 %). The GDP of Tianjin increased from US$117 million in 1978 to US$26 billion in 2017, with an average annual growth rate of 11.1 % in terms of comparable prices (Tianjin Statistics Bureau). According to the National Bureau of Statistics of China, Tianjin consumed 1.16 % of China's coal, 3.12 % of crude oil, and 1.47 % of electricity in 2014 (Qi, Dai, Geng, & Xie, 2018). Therefore, it is comprehensible that the GDP contribution of Tianjin is much higher than that of other cities. On the contrary, Xingtai presents the smallest

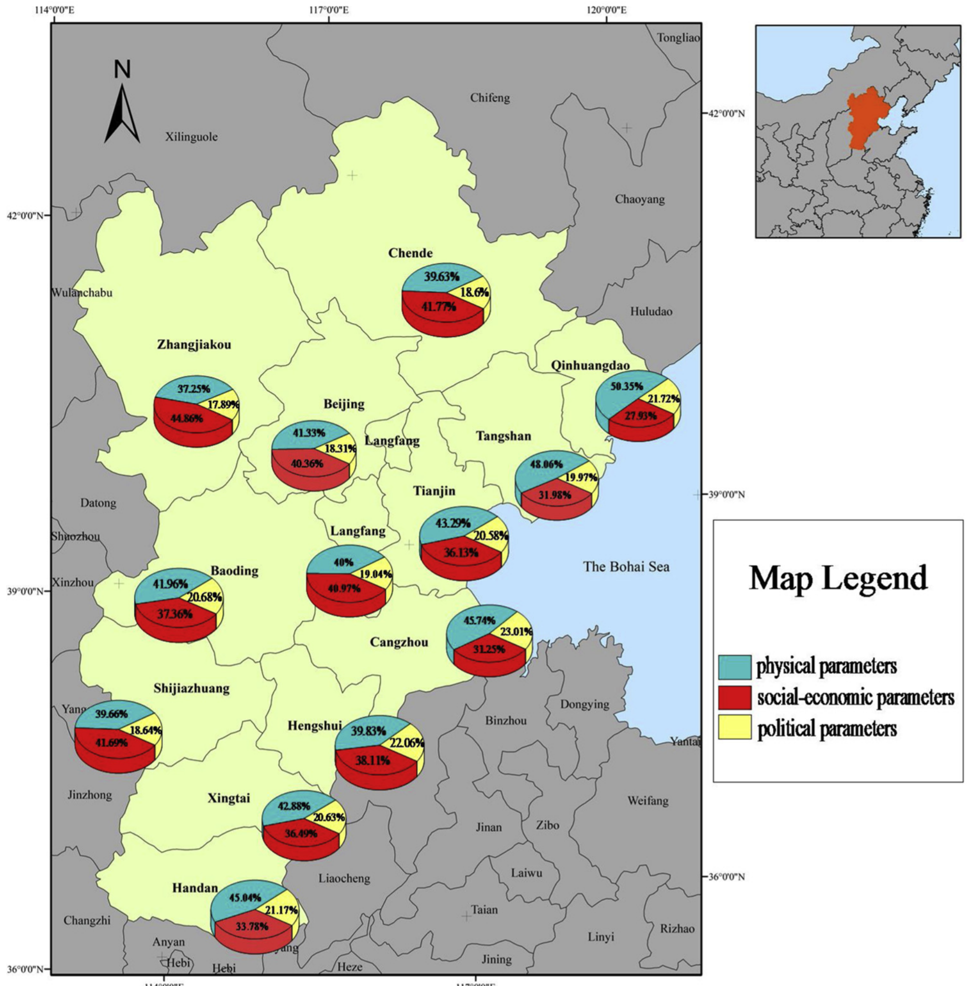

Fig. 6. The contribution of physical, socio-economic, and political parameters to urban drought vulnerability.

GDP proportion of UDV (11.5 %), followed by Hengshui (11.6 %). This was in connection with the underdevelopment economy.

5.2.2.3. Number of students enrolled in regular institutions of higher education. The cities where the number of students enrolled in regular institutions of higher education is one of the dominant factors of UDV are Qinhuangdao, Baoding, Cangzhou, Xingtai, Hengshui, and Handan. Cangzhou contributes the most, accounting for 17.1 %. Hengshui and Qinhuangdao both account for 15.1 %. The smallest contribution of the indicator to UDV is in Langfang (8.5 %), followed by Beijing (9.4 %). It is understandable that higher education rate implies strong mitigation and preparedness to drought hazards through direct and indirect channels (Hoffmann & Muttarak, 2017; Sharma, Patwardhan, & Patt, 2013). Obviously, higher and formal education signifies the increasing of technological innovation and predisposition to prepare against disasters (Hoffmann & Muttarak, 2017; Muttarak &

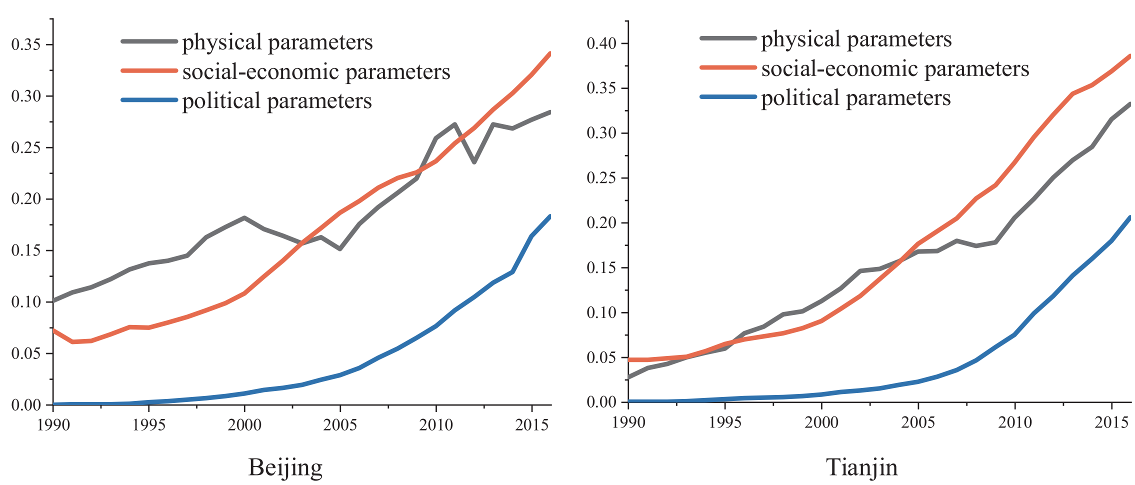

Fig. 7. The growth trend of physical, socio-economic, and political parameters in Beijing (left) and Tianjin (right).

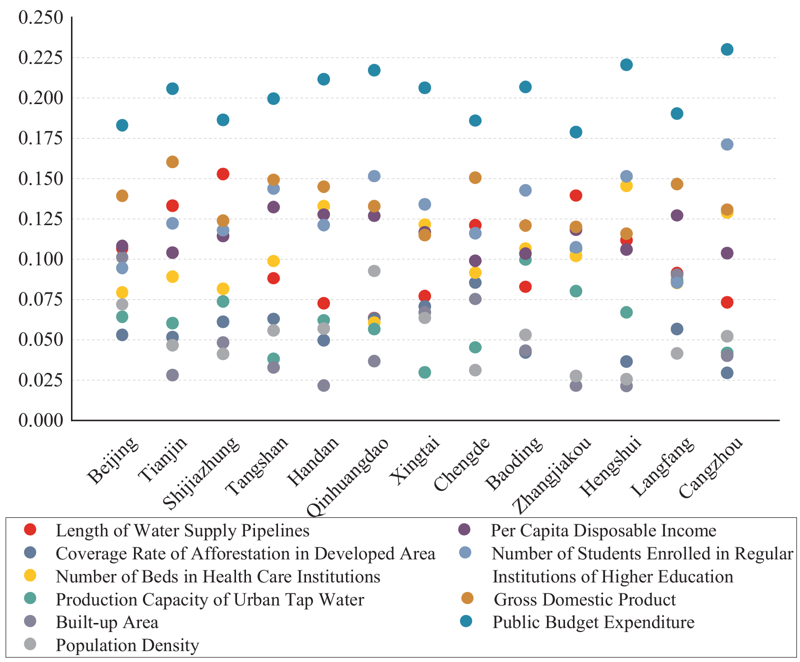

Fig. 8. Contribution of indicators to urban drought.

Lutz, 2014). From the analysis results, cities such as Cangzhou, Hengshui, and Qinhuangdao must intensely promote the development of education.

5.2.2.4. Length of water supply pipelines and number of beds in health care institutions. The length of water supply pipelines and the number of beds in health care institutions are also essential indicators. For the former, Shijiazhuang, Zhangjiakou, and Tianjin are the most heavily affected cities. For the latter, Hengshui, Handan, and Cangzhou were influenced observably. In contrast with the three indicators previously analyzed, these two indicators are directly related to UDV. The length of the water supply pipeline is an important factor in the coverage of urban water supply system and a decisive factor in the adaptability of urban infrastructure during a drought disaster. The number of beds in health care institutions is directly related to the accessibility of rescues and post-disaster adaptive capacity. Drought can have highly significant health effects on already distressed populations. In addition to decreased quantity and quality of potable water, drought can cause adverse effects on air quality related to prolonged particulate suspension in the air. There can aggravate bronchial passages, proliferate vector-borne diseases, etc. (McCann, Moore, & Walker, 2011).

6. Conclusions

Due to the lack of drought vulnerability studies in an urban level, this study evaluated and analyzed the UDV in the BTH region, considering the contribution of physical, socio-economic, and political parameters. The indexes and framework were appropriate for urban systems, which are significant in order to portray UDV. Moreover, the

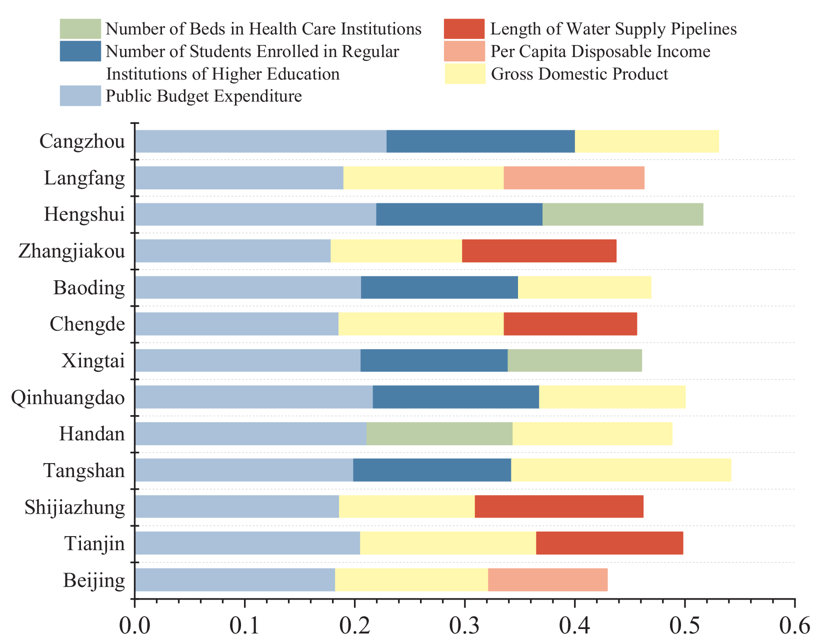

Fig. 9. Top three largest contributors to UDV in 13 cities.

contribution analysis from the parameter layer and index layer is conducive to explore the influencing factors and interaction of UDV.

The findings demonstrated that the BTH region is at a high level of drought vulnerability. The UDV of 13 cities in the BTH region increased from 1990 to 2016. In 2016, all cities were in a highly vulnerable state, wherein cities such as Tianjin are extremely vulnerable. Moreover, we concluded that more responsibility for high drought vulnerability should be attributed to social and economic factors. The economic development and population increase significantly increase the urban pressure during a drought disaster. The rapid economic development is being accompanied by inadequate physical infrastructure and ill-targeted policies, which contribute to a higher urban vulnerability.

Through the analysis of specific contribution of the index layer, we observed that indicators that significantly contribute to UDV are the following, in descending order by the number of cities affected: public budget expenditure, GDP, number of students enrolled in regular institutions of higher education, length of water supply pipelines, numbers of beds in health care institutions, and per capita disposable income. Exceptionally, public budget expenditure ranks first in all cities. Take Tianjin as example, few specific polices in Tianjin were dominant reasons of highest UDV. This suggests that the government should carefully consider drought disasters and enact more target policies.

This study analyzed the UDV of the BTH region and its influential factors. Based on the results, the interaction mechanism of cities in the BTH region should be explored in future studies, considering the systematism of cities.

Declaration of Competing Interest

The authors declared that they have no conflicts of interest to this work.

We declare that the manuscript “Urban drought vulnerability assessment- A framework to integrate socio-economic, physical, and policy index in a vulnerability contribution analysis” we do not have any commercial or associative interest that represents a conflict of interest in connection with the work submitted.

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