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Spatial Pattern Evolution and Influencing Factors of Cold Storage in China

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Abstract: Cold storage is the vital infrastructure of cold chain logistics. In this study, we analyzed the spatial pattern evolution characteristics, spatial autocorrelation and influencing factors of cold storage in China by using kernel density estimation (KDE), spatial autocorrelation analysis (SAA), and spatial error model (SEM). Results showed that: 1) the spatial distribution of cold storage in China is unbalanced, and has evolved from 'one core' to 'one core and many spots', that is, 'one core' refers to the Bohai Rim region mainly including Beijing, Tianjin, Hebei, Shandong and Liaoning regions, and 'many spots' mainly include the high-density areas such as Shanghai, Fuzhou, Guangzhou, Zhengzhou, Hefei, Wuhan, Ürümqi. 2) The distribution of cold storage has significant global spatial autocorrelation and local spatial autocorrelation, and the 'High-High' cluster area is the most stable, mainly concentrated in the Bohai Rim; the 'Low-Low' cluster area is grouped in the southern China. 3) Economic development level, population density, traffic accessibility, temperature and land price, all affect the location choice of cold storage in varying degrees, while the impact of market demand on it is not explicit.

Keywords: cold storage; spatial pattern evolution; kernel density estimation (KDE); spatial autocorrelation analysis (SAA); spatial error model (SEM); China

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1 Introduction

China is a big country in the production and consumption of agricultural products. Since 2004, the No.1 document by the Central Committee of the CPC (Communist Party of China) had focused on the three rural issues concerning agriculture, rural areas and farmers for 17 consecutive years (http://www.gov.cn/zhengce/wenjian/zhongyang.htm). However, the phenomenon of higher output of agricultural products not accompanying by a higher income still happens occasionally. At the same time, consumers often can not eat high quality food. These problems are caused partly by the incomplete cold chain facilities in China (Zhao et al., 2018). With the upgrading of household consumption and food safety awareness increasing, the demand for cold chain logistics is growing, and its market is gradually expanding in China. The market scale of cold chain logistics in

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China surged from 110 billion yuan (RMB) in 2012 to 339.1 billion yuan (RMB) in 2019 (Cui, 2020), and cold chain logistics is becoming more and more prominent in the national economy. Cold storage is the most important circulation node of cold chain logistics. The government in China has issued various policies to support the construction of pre cold storage in agriculture production area, cold storage to keep fruits and vegetables fresh and circulating cold storage, in order to improve the infrastructure network of cold chain logistics. On July 30, 2019, cold chain logistics were first mentioned by the Political Bureau of the CPC Central Committee, and the implementation of urban and rural cold chain logistics facilities. Therefore, how to layout the cold storage becomes an urgent problem.

Warehouse is an important carrier of logistics activities and the core unit of logistics nodes. It has the function of connecting production, circulation and consumption, creating time value and preserving commodity use value (Ye and Li, 2019). With globalization of the economy, the warehouse was playing an increasingly important role in the global value chain of products because the production and marketing are now separated (Jiang et al., 2016), which attracts scholars to study warehouse layout from different perspectives.

In recent years, based on location theory, external economic theory, new economic geography, evolutionary economics and other theories, scholars have carried out research on warehouse spatial layout (Devereux, 2004; Boschma and Frenken, 2011; Qian et al., 2011; Heuvel et al., 2013). Before the 1970s, the storage of goods was scattered. Multiple warehouses were located at the production and receiving locations, as well as intermediate warehouses (Allen, 2012), which resulted in many relatively small warehouses located in industrial areas and railway fields near the stations and piers in urban areas (Cidell, 2010). With the acceleration of urbanization, commodity flows have become highly concentrated in urban agglomerations and metropolitan areas such as San Francisco, Tokyo, Paris, Beijing, Shanghai (Li et al., 2017; Yuan, 2018; Zhang, 2018; Heitz et al., 2019; Sakai et al., 2019), which has led to an increase in the number of urban warehouses that have gradually gathered in metropolitan areas in order to form scale economic effect and provide better service for customers (Grazia, 2018; Heitz et al., 2018). However, the agglomeration of warehouse will lead to road congestion, cost increase, efficiency reduction and so on, so that the logistics enterprises give up the layout of warehouse in the agglomeration area (Heuvel et al., 2013). In addition, given the relatively low added value of warehouse, expansion warehouses are continuously moving from the city center to suburban areas and from developed urban agglomerations to surrounding city to maintain the high added value of the metropolitan center (Yuan and Zhu, 2019).

The research methods in the factors of influencing warehouse spatial distribution mainly include location mapping and correlation analysis (Bowen, 2008), weighted geographic mean (Dablanc, 2014), counting regression model (Holl and Mariotti, 2018) and so on, with few consideration about the spatial factors in modeling which is easy to cause estimation bias .They found traffic accessibility, the availability of land and its costs, the distance from the consumer market, government policy, regional economic strength, regional product output, population scale and other factors had a different influence on the location choice of warehouse (Boschma and Frenken, 2011; Verhetsel et al., 2015; Heitz and Beziat, 2016; Zhu et al., 2017; Heitz et al., 2018).

Because developed countries such as France, Germany, America and Japan have higher level of logistics marketization and intensification, the research data mostly adopts the logistics statistics data and enterprise sample survey data subdivided. However, the development of the logistics industry in China is still in its starting stage, and the logistics data is relatively scarce. In the early stage of China's logistics research, small sample questionnaires, yellow pages and other information were used, but this data have some problems, such as insufficient sample size and lack of information, which are difficult to meet the requirements of empirical analysis (Zhang et al., 2018). With the technological progress of location-based service providers such as Baidu, Tencent and other enterprises, Points of Interest (POI) ,which is a term in geographic information system and generally refers to all geographic objects that can be abstracted as points, including name, category, and coordinate, has been used in the logistics research (Li et al., 2017; Liu et al., 2018). However, POI is limited by too simple information, and the process and mechanism of spatial and temporal evolution of logistics facilities can not be explained more completely.

In recent years, the business registration data were gradually widely used based the with the development of data processing capability (Liu et al., 2018; Zhang et al., 2018). The data mainly include enterprise name, registered time, registered capital, registered address, enterprise type and business scope of the enterprise which have the characteristics of strong reliability, convenient for multi-scale and multi type analysis, and are the important basis for characterizing the level and ability of the main body of logistics market. This data has the advantages of large sample size, fast update speed and authority, which can more intuitively reflect the distribution, spatial structure and other characteristics of cold storage and better reflect the actual development of cold storage. Therefore, we will use the cold storage business registration data to analyze the dynamic evolution characteristics of cold storage spatial distribution. Then its driving forces are revealed based on the spatial econometric model with the panel data of 295 cities in 2008 2017. It is hoped that this paper provides decision support for government making policy planning and enterprises making development strategy.

2 Materials and Methods

2.1 Study area

The study area used in the kernel density estimation (KDE) of cold storage is 337 cities in China except for Hong Kong, Macao and Taiwan (Fig. 1). However, excluding county-level cities, as well as limited data of other variables, the 295 cities are used as the samples in the spatial autocorrelation analysis (SAA) and influencing factors regression analysis of cold storage. According to the Global Cold Chain Alliance (GCCA) statistics, the total capacity of cold storage was 105 million m^3 in China in 2018, ranking third in the world and accounting for 17% of the world (https://www.gcca.org).

2.2 Data sources and processing

The cold storage business registration data in this paper was mainly searched by selecting keywords such as 'cold storage', 'fresh storage', 'freezer', 'cold chain base' through websites of National Enterprise Credit Information Publicity System (http://www.gsxt.gov.cn/index.html) and Tianyancha (https://www.tianyancha.com), which mainly includes the name, year of establishment, registered address, registered capital,

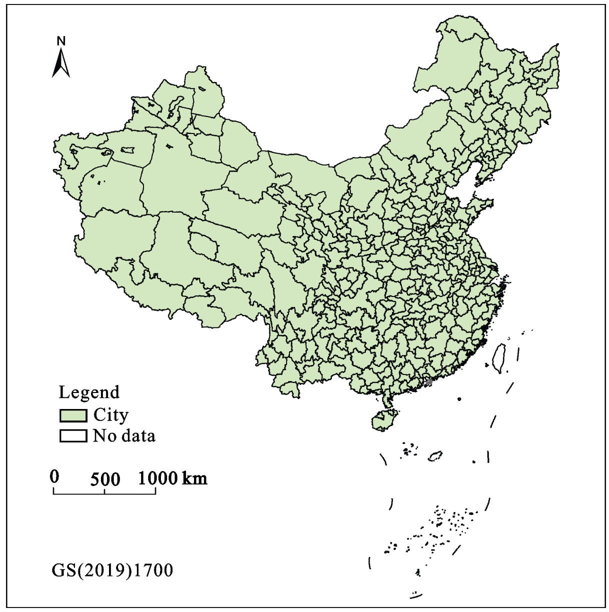

Fig. 1 Distribution of 337 cities in China used in this study. Hong Kong, Macao and Taiwan of China are no data

business scope and other information of cold storage. Totally, 14 705 cold storage data were finally obtained in December 2018. Then longitude and latitude of each cold storage can be obtained with XGeocoding software, a mass address longitude and latitude analysis and conversion tool, based on the address information of cold storage. The socio-economic data used in the spatial econometric model mainly come from *China City Statistical Yearbook* (National Statistics Bureau of China, 2009–2019), *China Land and Resources Statistical Yearbook* (Ministry of Natural Resources of China, 2009–2019); *China Statistical Yearbook For Regional Economy* (National Bureau of Statistics of China, 2009–2015), statistical yearbooks of 31 provinces, autonomous regions, and municipalities (2008–2017) (http://data.cnki.net/Yearbook), statistical yearbooks of 295 cities (2008–2017) (http://data.cnki.net/Yearbook), *National Economic and Social Development Statistics Bulletin of 295 cities* (2008–2017) (http://www.tjcn.org/tjgb/). Missing data are supplemented by interpolation and multiple regression prediction. In order to eliminate heteroscedasticity and skewness as much as possible and narrow the range of variable values, most of the variables are logarithmic.

2.3 Research methods

(1) Kernel density estimation

Kernel density estimation (KDE) is a common nonparametric method used for point data density visualization. When the search radius h is determined, different forms of kernel functions have less influence on the kernel density (Xue, 2019). We used the secondary kernel function of Silverman as follows (Silverman, 1986):

$$\hat{f}(x,y)=\frac{3}{nh^2\pi}\sum_{i=1}^{n}\left[1-\frac{(x-x_i)^2+(y-y_i)^2}{h^2}\right]^2 \quad (1)$$

where $\hat{f}(x,y)$ is the kernel density value at space position (x, y); h is the search radius (bandwidth); x_i and y_i are the longitude and latitude coordinates of cold storage i, respectively; n is the number of samples with a distance $\leq h$ from the position (x, y); and x, y represents the coordinates of the center point of the grid to be estimated in the bandwidth range.

(2) Spatial autocorrelation analysis (SAA)

In this study, spatial autocorrelation was used to analyze the spatial agglomeration of cold storage distribution, which was divided into global spatial autocorrelation and local spatial autocorrelation. Moran's index (Moran's I) is currently the most popular method for measuring spatial autocorrelation.

Global Moran's I is used to analyze global spatial features, which are calculated as (Gatrell, 1979; Li et al., 2012):

$$I=\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}(x_i-\overline{x})(x_j-\overline{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n}w_{ij}} \quad (2)$$

where I is the global Moran index, $S^2=\frac{1}{n}\sum_{i=1}^{n}(x_i-\overline{x})^2$ is the sample variance, x_i is the amount of cold storage in the areas, and w_{ij} is the (i, j) element of the spatial weight matrix. We used the classic binary queen adjacency matrix. The general value range of I is $[-1, 1]$. $I > 0$ indicates that there is a positive correlation; the high value is adjacent to the high value, and the low value is adjacent to the low value. $I < 0$ indicates that there is a negative correlation; the high value is adjacent to the low value.

Local indicators of spatial association (LISA) is the index of analyzing local spatial heterogeneity. We used the local Moran's I (Eq. 3) to identify different spatial association patterns, including 'High-High' clusters, 'Low-Low' clusters, 'High-Low' outliers, and 'Low-High' outliers (Anselin, 1993). The 'High-High' clusters were areas with high number of cold storage that were surrounded by neighboring areas also with high number of cold storage, while 'Low-Low' clusters were areas with low number of cold storage that were surrounded by neighboring areas also with low number of cold storage. These two patterns were positive spatial associations. In contrast, spatial outliers were identified when a region with high number of cold storage was surrounded by neighboring regions with low number of cold storage and vice versa.

The formula of local Moran's I is as follows (Anselin, 1995):

$$I_i=\frac{(x_i-\overline{x})}{S^2}\sum_{j=1}^{n}w_{ij}(x_j-\overline{x}) \quad (3)$$

where local Moran index I_i is similar to the global Moran index I. $I_i > 0$ indicates that the high (low) value of the areas is surrounded by a surrounding high (low) value; $I_i < 0$ indicates that the high (low) value of the areas is surrounded by the surrounding high (low) value, which is an abnormal value.

(3) Spatial econometric model

At present, there are three most commonly used spatial panel measurement models: spatial lag model (SLM), spatial error model (SEM) and spatial dubin model (SDM) (Anselin et al., 2004).

The SLM mainly studies whether the observed values of the dependent variables are related to the observed values of the adjacent areas, and its spatial heterogeneity is determined by spatial lag term. The mathematical expression of spatial lag is as follows:

$$y_{it}=\partial+\rho\sum\nolimits_{j=1}^{N}W_{ij}y_{it}+X_{it}\beta+\nu_i+\varphi_t+\varepsilon_{it}$$
$$\varepsilon_{it}\sim N(0,\sigma^2 I_n) \quad (4)$$

where ∂ represents the intercept term; ρ is the spatial correlation coefficient, reflecting the spatial linkage degree of the observed values of the dependent variables among different regions; X_{it} is the independent variables; β is the coefficient before the independent variable; ν_i is the spatial trait effect; φ_t is the temporal trait effect; ε_{it} is the random disturbance term; σ is the variance of the random disturbance term; I_n is the identity matrix. $\sum\nolimits_{j=1}^{N}W_{ij}y_{it}$ is the spatial lag term; y_{it} is the explained variable; W_{ij} is the spatial weight matrix. In this paper, based on the queen principle, the specific judgment standard is: if there is a public zone or public boundary between the two cities, it will be determined as the adjacent city, given $W_{ij} = 1$, otherwise $W_{ij} = 0$.

The SEM mainly studies the influence of error factors on regional economic activities, and its spatial heterogeneity is reflected by random disturbance terms. The expression is:

$$y_{it} = \partial + X_{it}\beta + \nu_i + \varphi_t + \mu_{it}$$
$$\mu_{it} = \lambda\sum_{j=1}^{N} W_{ij}\mu_{it} + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma^2 I_n) \tag{5}$$

where λ is the correlation coefficient of spatial error, which measures the influence of random disturbance term between regions on the dependent variables; μ_{it} is the spatial error term and is spatially dependent; $\sum_{j=1}^{N} W_{ij}\mu_{it}$ is the lag term of spatial error, which refers to the weighted average of the influence degree of error factors between regions on the dependent variables.

The SDM considers the spatial correlation of the dependent variable and independent variables, and its mathematical expression is

$$y_{it} = \partial + \rho\sum_{j=1}^{N} W_{ij}y_{it} + X_{it}\beta + \lambda\sum_{j=1}^{N} W_{ij}X_{it} + \nu_i + \varphi_t + \varepsilon_{it}$$
$$\varepsilon_{it} \sim N(0, \sigma^2 I_n) \tag{6}$$

2.4 Variables selection

Based on the relevant theory, existing literature (Jiang and Shi, 2015; Zhu and Zhou, 2017) and available data, the number of cold storage in cities (ln*wareh*) is selected as the dependent variable, and six influencing factors, such as economic development level, population density, market demand, traffic accessibility, climate conditions and land price, are selected to analyze the influence mechanism of spatial layout of cold storage in China by using spatial econometric model (Table 1). The specific independent variables and definitions are as follows.

Economic development level (ln*pgdp*): the spatial location choice of warehouse is deeply affected by the overall economic strength of the region (Qian et al., 2011). When the overall strength of the regional economy is strong, more production and logistics needs are generated, accelerating the accumulation of warehouse in such areas. The concentration of warehouse also drives the growth of the regional economy, and forms hub economy. GDP per capita is used to represent the regional economic development level.

Population density (ln*popd*): as early as 1921, the U.S. Department of Agriculture conducted a survey of the national cold storage, which showed that cold storage was mainly concentrated in areas with a large population (Banks, 1954). Cold storage located in densely populated areas can reduce the cost of labor search, where there are abundant labor resources and a large demand for cold storage.

Market demand (ln*dem*): Liu et al. (2017) found that demand is an important driving factor of star warehouse layout through the study of location choice behavior of star warehouse in China. Generally speaking, regions with big quantity fresh product output and fresh product consumption have a large demand for cold storage. Market demand is expressed by the sum of regional fresh product output and fresh product consumption.

Traffic accessibility (ln*roadp*): by analyzing the spatial distribution of logistics facilities in the United States, Spain, and Belgium, warehouse layout is closely related to the accessibility of highways, aviation, and ports, but the correlation with railway accessibility is low (Bowen, 2010; Verhetsel et al., 2015; Holl et al., 2018). The convenient transportation conditions can be convenient for goods turnover. Therefore, traffic accessibility is expressed by the density of regional roads.

Climatic conditions (*tem*): natural conditions are the most basic factors affecting warehouse location (Mo and Qian, 2010). Different climate conditions may affect the production of fresh products, residents' consumption of fresh products, construction and operation costs of cold storage, the climate expressed by temperature may have an influence on its choice for cold storage location.

Land price (ln*ltp*): logistics activities have been requiring increasingly larger buildings (Mckinnon, 2009), which necessitates a large amount of land. Considering the low profit margin of logistics activities, logistics facilities are often located in the areas surrounding the city where the land supply is adequate and the price is low (Heitz and Beziat, 2016). Verhetsel et al. (2015) found that land rent is the most important factor affecting the location choice of logistics facilities. To reduce the cost of transportation, a balance must be found between land cost

Table 1 Descriptive statistics of variables

Variables	Unit	Mean	SD	Min.	Max.
ln*wareh*		1.774	1.451	0.000	6.931
ln*pgdp*	yuan (RMB)/person	10.450	0.655	8.189	13.060
ln*popd*	person/km^2	5.619	1.153	0.485	8.766
ln*dem*	10000 t	5.738	0.896	2.054	8.177
ln*roadp*	km/10000 people	3.409	0.631	0.266	5.880
tem	℃	14.841	5.166	–2.200	27.000
ln*ltp*	10000 yuan (RMB)/ha	6.473	0.881	1.698	10.300

Notes: The parameters explanation can be seen the section above Table 1. SD is the standard deviation of the data

and transportation operation cost to select the best position with the lowest total cost (Heitz and Beziat, 2016). The land price is expressed by land transaction price.

3 Results

3.1 Spatial pattern and evolution characteristics of cold storage

The kernel density is one way to convert a set of points into a raster. The high kernel density means that the cold storage has a high degree of aggregation, otherwise, the cold storage has a low degree of aggregation. The kernel density of China's cold storage was estimated using ArcGIS10.6 based on Equation (1) (Fig. 2). How to set the search radius is a key issue when analyzing the cold storage kernel density, which affects the kernel density result and map visualization. After repeated experiments, the search radius was finally determined to be 110 km.

In Fig. 2, the overall spatial distribution of cold storage in China has evolved from 'one core' to 'one core and many spots'. From 2008 to 2013, the spatial distribution pattern of cold storage did not have many changes, and the high value areas of kernel density are mainly concentrated in 'one core', that is, the Bohai Rim region, mainly including Beijing, Tianjin, Hebei, Shandong and Liaoning regions, and the nuclear density values of cold storage in other regions are relatively low. In 2018, the spatial distribution pattern of cold storage extends southward to the junction of Shandong, Henan and Anhui provinces. Based on the original 'one core', and begin to appear many high-density areas such as Shanghai, Fuzhou, Guangzhou, Zhengzhou, Hefei, Wuhan, Ürümqi.

ArcGIS10.6 was used to calculate the global Moran's I value of cold storage for 295 cities based on Equation (2) (Table 2). Global spatial correlation of cold storage between prefecture level cities in China in 2008–2018 is very significant ($P < 0.01$) and shows a strong positive correlation. It means cities with a large amount of cold storage are adjacent to each other, and cities with a small amount of cold storage are also adjacent to one another.

The cross-sectional data of 2008, 2013 and 2018 are selected to reflect the agglomeration heterogeneity of cold storage in different cities with Lisa agglomeration map of local Moran index. The Lisa agglomeration map of cold storage in typical years in China is drawn with ArcGIS software (Fig. 3). The most stable 'High-High' cluster areas mainly concentrated in the Bohai Rim, which include Beijing-Tianjin-Hebei region, Shandong

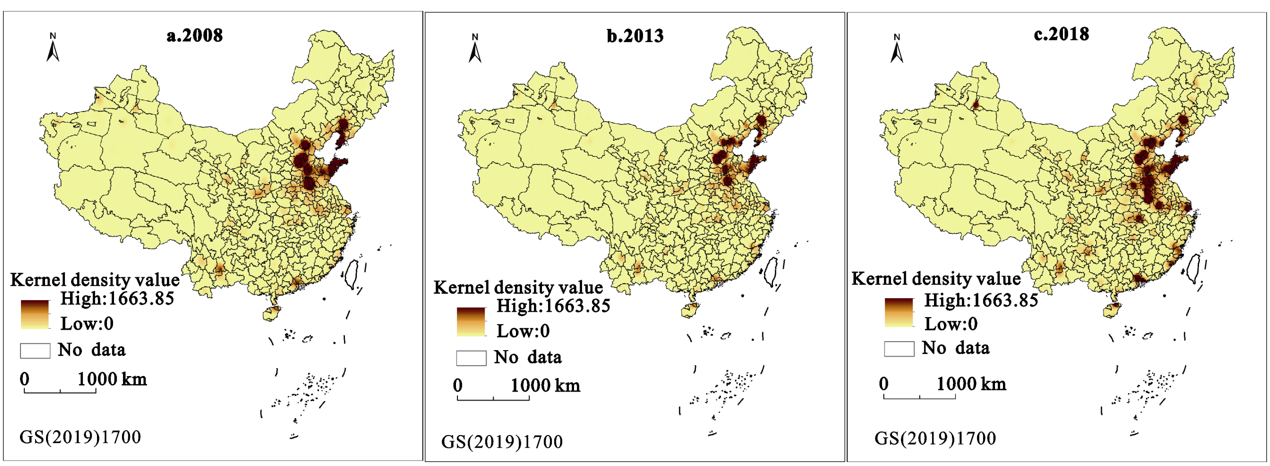

Fig. 2 Kernel density of cold storage in China in 2008, 2013 and 2018

Table 2 Global Moran's *I* test results of cold storage in 2008–2018

Year	Moran's *I*	Variance	*Z*	*P*
2008	0.198	0.001	8.008	0.000
2009	0.171	0.001	7.077	0.000
2010	0.162	0.001	6.903	0.000
2011	0.168	0.001	0.001	0.000
2012	0.160	0.001	6.863	0.000
2013	0.155	0.001	6.679	0.000
2014	0.164	0.001	6.912	0.000
2015	0.174	0.001	7.190	0.000
2016	0.184	0.001	7.460	0.000
2017	0.196	0.001	7.793	0.000
2018	0.202	0.001	7.954	0.000

Province and Liaoning Province. The number of cold storage in these cities is higher than that in their surrounding cities. It belongs to the area of high quantity homogeneity. The 'Low-Low' cluster area is grouped in Anhui, Jiangxi, Hubei, Hunan, Guangxi, Sichuan, Chongqing, Guizhou and other provinces in southern China. The number of 'Low-Low' cluster cities reduces from 93 in 2008 to 71 in 2018. These areas of low quantity and homogeneity are characterized by continuous distribution, and the number of cold storage in the city and its surrounding cities is low and positively correlated. The 'High-Low' cluster area is unstable, scattered in Haikou, Shanghai, Lanzhou, Wuhan, Harbin, Chengdu and other cities. A large difference between the amounts of cold storage in these cities is quite different from that of its surrounding cities. Although the number of cold storage in the cities is relatively high, it does not stimulate the development of the surrounding cities. The number of cold storage in the surrounding cities is low, forming a 'polarization type' spatial layout which features with high number in the middle and low number in the surrounding areas. The 'Low-High' cluster area is adjacent to 'High-High' cluster area, which include Chengde, Langfang, Datong, Yangquan, Dongying, Binzhou, Puyang, Shangqiu and other cities. The number of cold storage in this type of city is quite different from that in the surrounding cities. The number of cold storage in this type of city is more, while the number of cold storage in the surrounding cities is more, which is low in the middle and in its surrounding cities. The spatial pattern shows the negative correlation characteristics which is low number in the middle and high number in its surrounding cities.

3.2 Empirical analysis of factors influencing spatial distribution of cold storage

Because of the serious lack of research data in 2018, in order to ensure the reliability of the research results, we use the panel data of 2008–2017 in 295 cities to analyze the influencing factors of the spatial distribution of cold storage.

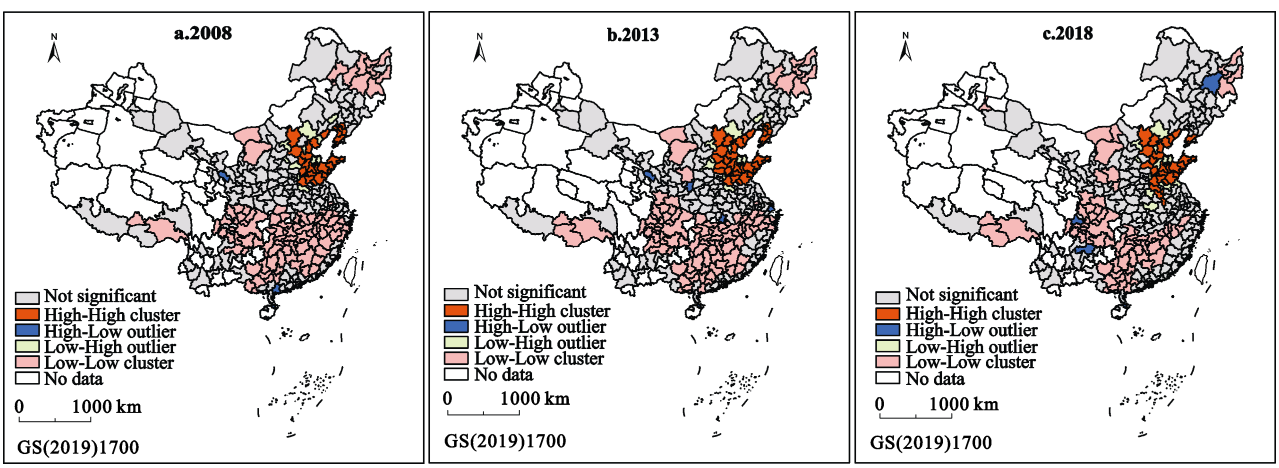

Fig. 3 Local indicators of spatial association (LISA) map of cold storage distribution in China in 2008, 2013 and 2018. High-High and Low-Low represent statistically significant clusters of high and low cold storage distribution, whereas High-Low and Low-High are outliers representing either high cold storage distribution surrounded by cold storage distribution, or vice versa

3.2.1 Model selection

In the selection of spatial econometric models, the criteria proposed by LeSage and Pace are generally used (LeSage and Pace, 2009): first, the Lagrange multiplier (LM) significance levels of SLM and SEM were compared and the model with a higher significance level was selected; if the LM level of significance of SLM and SEM was comparable, a model with a high level of robust LM significance was selected. According to the LM test results (Table 3), the LM statistic of SEM and SLM are significant at the 0.01 level. Then, the robust LM statistic of SEM is significant at the 0.05 level, but the robust LM statistic of SLM is not significant at the 0.05 level. Therefore, the SEM is chosen for this research.

3.2.2 Regression analysis

Likelihood ratio (LR) test results show that spatial error model (SEM) with spatial-time double fixed effect should be selected to estimate model parameters. The estimation results of factors influencing cold storage layout in China are shown in Table 4.

According to Table 4, most of the factors coefficients are positive and statistically significant at 0.05 level. This means that these factors are positively correlated with number of cold storage. The economic development (ln*gdp*) creates a substantial demand for the development of cold chain logistics and promotes the infrastructure construction, such as cold storage. Positive correlation between population concentration level (ln*popd*) and number of cold storage is also supported by previous study (Banks, 1954). In addition, with the process of urbanization, more and more people gathered in urban area and speeded the population density in urban, but supply of fresh products is still in rural areas, the spatial distribution contradiction between supply and demand promote the infrastructure construction of cold chain logistics. High road density (ln*roadp*) improves the convenience of the fresh products transportation and drive the construction of cold storage in different concentrated regions of fresh products. Due to the perishability of fresh products, it needs to be concentrated and dispersed quickly. Since the development of logistics industry, transportation infrastructure and location accessibility are always important factors affecting its layout. With the progress of urbanization, the transportation infrastructure is constantly improving, and the land cost and labor cost in the city center are constantly rising, the cold storage will spread from the city center to the suburbs along the transportation trunk line. Moreover, this study found that land cost (ln*ltp*) is positively related to the spatial distribution of cold storage. Cold storage tends to be distributed in areas with higher land prices, which seems to be inconsistent with common sense. However, this means that cold storage are mainly concentrated in more developed areas, where the land price is relatively high, but enterprises can enjoy preferential policies, have technical advantages, and larger demand for cold storage. This is not contradictory to the fact and we can see that cold storages are mainly located in the suburbs of cities.

Table 3 Lagrange multiplier (LM) test of the spatial measurement model

Model	Test	Statistic	df	*P*-value
Spatial error	Moran's *I*	0.817	1	0.414
	Lagrange multiplier	14.454	1	0.000
	Robust Lagrange multiplier	5.139	1	0.023
Spatial lag	Lagrange multiplier	10.020	1	0.002
	Robust Lagrange multiplier	0.705	1	0.401

Table 4 Ordinal least squares (OLS) and spatial error model (SEM) estimation and test results

Variables	OLS		SEM with spatial fixed-effects		SEM with time fixed-effects		SEM with spatial and time fixed-effects	
	Coefficients	Standard errors	Coefficients	Standard errors	Coefficients	Standard errors	Coefficients	Standard errors
ln*pgdp*	0.402***	10.95	0.827***	22.58	0.199***	5.03	0.132***	2.94
ln*popd*	0.174***	4.59	0.787***	9.77	0.151***	3.82	0.172**	2.26
ln*dem*	0.721***	23.83	0.031	0.60	0.709***	25.76	0.036	0.76
ln*roadp*	0.146**	2.37	0.710***	11.04	–0.105*	–1.67	0.202***	3.32
tem	0.061***	–13.96	0.078***	5.33	–0.063***	–13.53	–0.043***	–3.07
ln*ltp*	0.279***	8.69	0.114***	7.15	0.159***	4.81	0.032**	2.15
cons	–8.949***	–18.19						
λ			0.344***	12.71	–0.042	–1.56	0.155***	6.30

Notes: ***, ** and * were significant at 0.01, 0.05 and 0.10 respectively

Negative correlation between the regional temperature (*tem*) and the spatial distribution of cold storage is found. There may be two reasons for this result. First, when the temperature rises, cold storage consumes more energy. Large-scale cold storage may be established to reduce energy consumption, so the amount of cold storage may decrease. In addition, when the temperature rises, fresh food is prone to deterioration. Residents' consuming behavior of fresh agricultural products tends to high frequency, small batch, which accelerates the flow of fresh food. For this reason, less cold storage is needed.

The impact of market demand (ln*dem*) on the amount of cold storage is not explicit. The probable reason for this result is that the development of cold chain logistics lags behind the development of fresh products industry. Moreover, substantial fresh products did not process with cold chain logistics. This result needs study in-depth in the future research.

In the spatial error model (SEM), λ value is significant at 0.01 level. This shows that the development level of cold storage is not only affected by the level of regional economic development, population scale, road density, land cost, regional temperature and other observable factors, but also by the unobservable factors of its adjacent areas, which may include policies, eating habits, *etc*.

4 Discussion

Cold storage is the most important cold chain logistics infrastructure, and their spatial layout directly affects the development of cold chain logistics. The spatial distribution characteristics of different warehouse types are diverse (Heitz and Beziat, 2016). Therefore, a study of cold storage spatial layout and influencing factors is of great significance to optimize the industrial layout, improve the operation efficiency and broaden the spatial layout theory of logistics facilities. Compared with the data of questionnaire, yellow pages and POI, the business registration data has many advantages, such as large sample size, fast update speed, with time attribute , so the use of business registration data can identify the spatial pattern evolution of cold storage more effectively to optimize the spatial layout of cold chain logistics.

We found that the influencing factors of regional cold storage quantity are general, similar to those of general warehouses. For example, economic development and traffic accessibility has positive influence to warehouse (cold storage). At the same time, the influencing factors of cold storage spatial distribution also have certain particularity. Compared with ordinary warehouses, the temperature has a greater impact on the distribution of refrigerators, that is, the higher the annual average temperature is, the less cold storage are. This has been analyzed above, mainly for two reasons. What's more, population scale has a positive impact on the distribution of cold storage in China, which is the same as that in the United States. Market demand is an important factor for the spatial distribution of cold storage in the United States, but the impact of market demand on the spatial distribution of cold storage in China is not explicit (Banks, 1954). The main reason is that China's cold storage development is relatively lagging behind, coupled with high construction costs, leading to market willingness of building cold storage may not being strong enough.

In this paper, the characteristics of spatial distribution and evolution of cold storages in China are revealed only by approximate 'big data' of cold storages. As the main body of cold chain logistics, cold storage location and spatial distribution are affected by many factors. Limited to the current data and information, the micro mechanism of the location selection of various cold storages, relationship between different cold storage, government policy factors have not been fully analyzed and explained, and further efforts should be made in the future follow-up research. In addition, to judge the development level of cold storage only by the amount of cold storage is prone to bias. The capacity of a large cold storage may be much larger than that of several small cold storages. In the future, it is necessary to improve the properties of cold storage service objects further, strengthen the connection with economic census data, and deepen the logistics location theory.

Based on above research, we can obtain three policy enlightenments. Firstly, the government should strengthen the construction of cold storage. At present, the total amount of cold storage is small, and the spatial distribution of cold storage is extremely uneven. Except for the Bohai Rim region and some big cities, the number of cold storage in other regions is very small. The government shall support the upgrading or elimination of the old cold storage, the construction of new air-conditioned cold storage, three-dimensional automatic cold storage, multi temperature layer large-scale cold storage and other intelligent high-end cold storage, and give support in planning, land, capital and other aspects (Zhang, 2019). Second, cold storage resources should be integrated. The heterogeneity of cold storage spatial distribution requires that cold storage should be built according to local conditions. The regional cold storage resources should be integrated, large-scale cold storage should be built in the 'High-High' cluster areas, and cold storage facilities and equipment should be shared, in order to form scale effect and improve the serving level of cold chain logistics. The regional cold storage with big cities as the core to serve the surrounding areas should be built in 'High-Low' concentration areas (Zhang and Zhang, 2018). Finally, it is necessary to increase the propaganda of cold chain logistics and improve consumers' awareness to cold chain logistics. Although the food guaranteed by the cold chain has better quality, due to the high logistics cost and high price, there may be a clear appearance of 'bad money drives good money out of circulation'. Therefore, the cold chain logistics demanding market will be getting bigger and bigger by improve consumers' awareness to cold chain logistics.

5 Conclusions

Cold storage is the most important infrastructure of the cold chain logistics, which can guarantee food safety and promote consumption upgrading. Based on kernel density estimation (KDE), we analyzed the characteristics of spatial distribution and evolution of cold storage in China. Then, it is revealed that the regional agglomeration heterogeneity of cold storage with Moran' *I*. Finally, we studied the influence factors of cold storage spatial distribution by building SEM. The conclusions are summarized as follows:

(1) With the rapid increase of the number of cold storage, the location choice of cold storage in China shows certain stability and imbalance. Stability refers to that the cold storage cluster center is relatively stable from 2008 to 2018, mainly concentrated in the Bohai Rim region. The imbalance refers to that, except for Bohai Rim region, the number of other areas is relatively small, but there have been some gathering points gradually such as Shanghai, Fuzhou, Guangzhou, Zhengzhou, Hefei, Wuhan, Ürümqi.

(2) Based on Moran' *I*, we found the distribution of cold storage has significant global spatial autocorrelation and local spatial autocorrelation. The 'High-High' cluster area is the most stable, mainly concentrated in the Bohai Rim; the 'Low-Low' cluster area is grouped in southern China.

(3) From the perspective of the influencing factors of the spatial distribution of cold storage in China, economic development, population density, traffic accessibility and land price has a positive significant influence to the location choice of cold storage at 0.05 level. Negative correlation between the regional temperature (*tem*) and the spatial distribution of cold storage is found. However, the impact of market demand on the amount of cold storage is not explicit.

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