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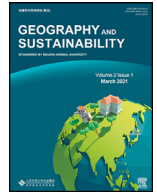
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## Research Article

# Evolving patterns of agricultural production space in China: A network-based approach

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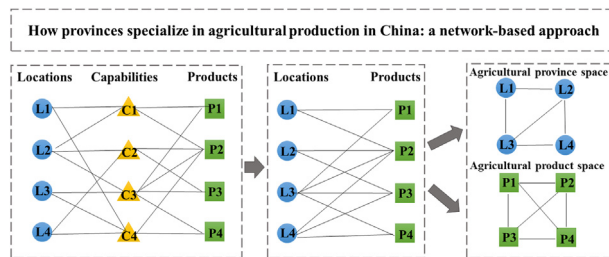
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## HIGHLIGHTS

- Agricultural production space is characterized by bipartite network.
- Product and province spaces exhibit well core-periphery and community structures.
- The community changes show relatively stable production patterns.
- The study offers a holistic view to understand agricultural production system.

## GRAPHICAL ABSTRACT



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## ABSTRACT

The agricultural production space, as where and how much each agricultural product grows, plays a vital role in meeting the increasing and diverse food demands. Previous studies on agricultural production patterns have predominantly centered on individual or specific crop types, using methods such as remote sensing or statistical metrological analysis. In this study, we characterize the agricultural production space (APS) by bipartite network connecting agricultural products and provinces, to reveal the relatedness between diverse agricultural products and the spatiotemporal characteristic of provincial production capabilities in China. The results show that core products are cereal, pork, melon, and pome fruit; meanwhile the milk, grape, and fiber crop show an upward trend in centrality, which is in line with diet structure changes in China over the past decades. The little changes in community components and structures of agricultural products and provinces reveal that agricultural production patterns in China are relatively stable. Additionally, identified provincial communities closely resemble China's agricultural natural zones. Furthermore, the observed growth in production capabilities in North and Northeast China implies their potential focus areas for future agricultural production. Despite the superior production capabilities of southern provinces, recent years have witnessed a notable decline, warranting special attentions. The findings provide a comprehensive perspective for understanding the complex relationship of agricultural products' relatedness, production capabilities and production patterns, which serve as a reference for the agricultural spatial optimization and agricultural sustainable development.

## 1. Introduction

As part of the United Nations Sustainable Development Goals (SDGs), the Chinese Government has given priority to ending hunger and ensuring sufficient food supply, achieving food system sustainability (Agnolucci et al., 2020). Driven by population growth and economic

development, dietary structures have changed with people consuming numerous and diverse food than ever before (Sun et al., 2019). Simultaneously, there is limited arable cropland in China, with over 40% of it classified as “moderately” or “severely” degraded, due to issue such as soil erosion, water pollution, or water scarcity (Sommer et al., 2023). The combination of these factors puts certain pressure on agri-

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cultural production in China (Ye et al., 2022). The agricultural production space, as where and how much each agricultural product grows, plays an important role in satisfying the increasing and diversified food demands.

China's agricultural production capability stands as a critical determinant in maintaining nation's future food supply. It is affected by multiple factors, including land and water resources (Duan et al., 2021), climate (Arora, 2019), households' land-use behaviors (Liu et al., 2020), fertilizer and pesticide inputs (Seghezzo et al., 2020; Yu et al., 2021), management practices (Cui et al., 2018), as well as national policies and strategies (Lu et al., 2022). These factors are prior notions of what are the important factors of agricultural production. However, it is not easy to embrace all factors and to quantify all factors or components of agricultural production capability (van Ittersum et al., 2008). Instead, according to the agnostic approach, an outcomes-based approach offers an alternative way to measure production capability. This approach has been used in the international trade field, where a country's export goods could reveal its domestic production capabilities and specialization patterns (Sciara et al., 2020). In agricultural production, the output of agricultural products can serve as a reflection of the production capability of a particular region. The fact that the production of identical agricultural products across different regions may suggest a shared production capability to cultivate these products. Agricultural products are seen as a consequence of a region's or province's endowments or capabilities, possibly covering land, water resource, labor, technology, knowledge and capital (Antle et al., 2004; Gumbau Albert, 2017).

Analyzing agricultural production system has been proved to be a complex task due to its interrelated and heterogeneous characteristic (Jones et al., 2017). Previous studies such as crop distribution and its spatial optimization (Hu et al., 2022; Q. Liu et al., 2022), crop yields (Wang et al., 2022), crop production conditions (Pickson et al., 2022) and so on have been carried out. There are also numerous researches about the structure and space of agricultural production in China, such as spatiotemporal characteristics of agricultural production efficiency (Guo et al., 2020), spatial feasibility and cost-effectiveness of agricultural land consolidation (Duan et al., 2021), productivity and environmental costs of different-scale farms (Qi et al., 2018), the pattern of product diversification (Emran and Shilpi, 2012). Statistical metrology (Baldoni and Esposti, 2020) and remote sensing with GIS (Medennikov et al., 2020) are commonly used in these fields. However, these studies mainly focus on single agricultural product or some specific products (Geng et al., 2017). Interrelation among diverse agricultural products in the whole nation is rarely explored. Furthermore, currently spatial mismatch continues to exist between major producing area, agricultural production structure and farmland resource in China (Li et al., 2017). Analyzing single agricultural product alone poses challenges in effectively integrating various agricultural activities and production capabilities, thereby hindering the optimization of agricultural layout (Lu et al., 2013).

Recently, complex network (CN) has been introduced into agricultural field. For example, Branco et al. (2021) used network approach to optimize the spatial distribution of new soybean and corn in Brazil. Ma et al. (2019) developed a network with 502 farms in the UK to compare resilience of genetically modified herbicide-tolerant management and conventional weed management. Z. Chen et al. (2022) applied a spatial network framework to analyze the cross-regional collaborative mechanisms for agricultural green development in China. Moreover, complex network approach also has been used to measure countries' specialization patterns and analyze how these patterns affect food supply and food security in global food system (Campi et al., 2020, 2021). Combining complex network with global agricultural products is used to explore why and how a country produces goods, proposing that a country's ability to produce new goods is constrained by the combination of its existing capabilities and the acquisition of novel capabilities

(Hidalgo and Hausmann, 2009). The global agricultural product space can also reveal the relatedness between diverse products and find different structures in different network locations (Hidalgo et al., 2007). Complex network is extensively applied in varieties of real-world systems, such as agriculture system (Albert and Barabási, 2002; Mariani et al., 2019), which can help to simulate interconnections among diverse agricultural elements and capture dynamic characteristics of agricultural system, providing a new perspective and an effective tool to study complex systems (Lambiotte et al., 2019).

In this study, we use complex network approach to characterize China's agricultural production space, and identify core-periphery structure and community structure of agricultural product space and province space, revealing the relatedness of multiple agricultural products and the spatial characteristic of provincial production capabilities. This work provides a systematic and holistic perspective to investigate agricultural production space and structure, offers us a better understanding of the complex relationship of agricultural production space and production capability, and the relatedness of diverse agricultural products. It is significant reference to upgrade and diversify agricultural product bundles in China to achieve the spatial optimization of agricultural production. We will address the following questions in this study:

- What characterizes the “province-product” agricultural production space in China from 1995 to 2019, and what are the structures and patterns of agricultural product space and province space?
- What is the relatedness of multiple agricultural products and the spatial characteristic of provincial production capabilities under current production structure?

## 2. Materials and methods

### 2.1. Theoretical background of complex network

Complex network serves as a type of graph that can abstract activities or event into elements and their relations (Lacasa et al., 2008). Within the network framework, elements are assigned as nodes, meanwhile connection or relationship between pairs of elements are regarded as links. In this study, we use complex network connecting provinces and agricultural products to build a series of agricultural production space in China. The fact that different provinces producing the same products might indicate that they share possession of the required essential capabilities for producing these goods (Fig. 1(a)).

When two agricultural products share similarities in terms of essential requirements such as climate, soil, water, technology, and other pertinent factors, they tend to be cultivated together in the same regions. Conversely, dissimilar agricultural products exhibit a lower likelihood of co-production (Fig. 1(b)). Measuring the similarity of capabilities required for products and the similarity of endowment of provinces are called “proximity” in the complex network approach. Proximity matrix connects pairs of agricultural products yielding the “product space” (Hidalgo et al., 2007). Equally, proximity matrix can also link pair of locations, giving rise to “province space” (Bahar et al., 2014). The proximity of product space and province space is built as proximity network to reveal distinct agricultural network characteristics in China (Börner et al., 2012; Balland and Rigby, 2017). Despite their specific structures, proximity network serves as a foundation for measuring the relatedness among agricultural products (Hidalgo et al., 2007). In this study, agricultural product network is projected into agricultural province space and product space by proximity matrix (Fig. 1(c)).

### 2.2. Data

Data on agricultural production from 1995 to 2019 for all 31 provinces are sourced from the National Bureau of Statistics in China

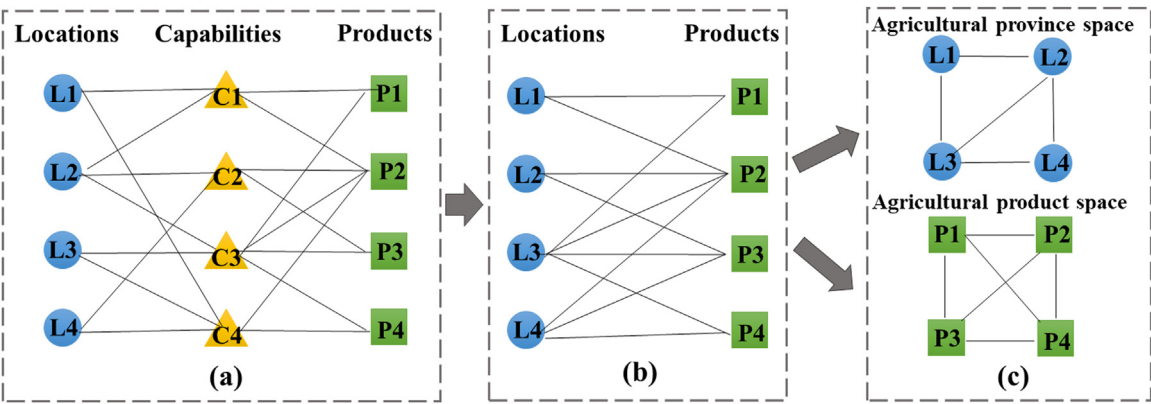


Fig. 1. Theoretical map of the complex network in agricultural production.

Table 1  
Categories of agricultural products at Levels 1, 2 and 3.

Level 1	Level 2	Level 3				
Cereal	Wheat Maize Rice Sorghum Barley Millet					
Vegetable and melon	Melon	Watermelon				
Fruit and nut	Tropical and subtropical fruit Citrus Grape Berry Pome fruit	Banana	Muskmelon			
	Soybean Peanut		Pineapple			
Oil crop	Temporary oilseed crop					
Root crop	Potato	Flaxseed	Rapeseed	Sesame	Sunflower seed	
Irritant and spice crop	Irritant crop	Tea				
Bean	Mung Adzuki					
Sugar crop	Sugar beet Sugarcane					
Livestock product	Beef Mutton Pork Milk Poultry egg Honey					
Aquatic product	Seawater product Freshwater product					
Others	Fiber crop Tobacco	Cotton	Sisal	Jute	Flax	Ramie

Sources: Bureau of Statistics in China (<https://data.stats.gov.cn/easyquery.htm?cn=E0103>); the World Agriculture Census Program in 2020 of the FAO (<https://www.fao.org/world-census-agriculture/wcarounds/wca2020/en/>).

(NBSC). Product classification is conducted following the Revised Indicative Crop classification from the World Agriculture Census Program in 2020. This classification categorized all agricultural products into three main types, as outlined in Table 1. The Level 1, consists of 11 groups, while the more detailed Level 2 includes 31 specific products. For the purposes of this study, Level 2 products are used due to their increased specificity. In case where NBSC does not directly provide data on certain products, we calculate them from data in Level 3. As shown in Table 1, the products are melon, tropical and subtropical fruit, berry, pome fruit, temporary oilseed crop, irritant crop, and fiber crop. All data of the selected agricultural products are completely recorded in 31 provinces from 1995 to 2019. During this period, the recorded data of each product remains stable, with rare missing values. The proportion of each agricultural product is also demonstrated, which is in line with China’s food production situation (Fig. S1, Fig. S2).

2.3. Methods

2.3.1. Agricultural production space

To explore how province grows agricultural production, we adopt the complex network to build agricultural production space, as introduced by Campi et al. (2020). This approach enables the representation of the relationship between provinces and agricultural products. The specific type of complex network in this study is bipartite network which is described as a bipartite matrix  $M$ . Within this framework, bipartite network, designated as a triplet  $G = (C, P, X)$ , consists of three components:  $C$ , representing the set of top nodes corresponding to provinces;  $P$ , signifying the set of bottom nodes corresponding to agricultural products;  $X$ , denoting the set of links. The specific element  $X_{ik}^t$  indicates that the province  $i$  produces product  $k$  in year  $t$ . We constructed the APS with agricultural products at Level 2 from 1995 to 2019 over 31 provinces.

### 2.3.2. Link weight

The link between two nodes within the APS indicates that the specific province produces the specific agricultural products. Moreover, the weight assigned to each link serves as an indicator of the province's capabilities or abilities concerning that particular product. With the theory of an outcomes-based method, we use the data of final agricultural products to calculate capabilities or performance of this province in producing a particular agricultural product. It is identified as follows:

$$M_{i,k}^t = \frac{x(i,k)}{\sum_k x(i,k)} \times \frac{\sum_i x(i,k)}{\sum_{i,k} x(i,k)} \quad (1)$$

where,  $x$  is production;  $x(i,k)$  is the production of product  $k$  in province  $i$  in year  $t$ . The first fraction is the ratio of the production of product  $k$  in that of all products in province  $i$ , and the second fraction is the proportion of a given product  $k$  among all products in China.

### 2.3.3. Proximity matrix

In the network-based approach, relatedness captures the interactions among elements that are similar, which quantifies these relatedness or similarity call 'proximity' (Hidalgo et al., 2007). Proximity matrix can evaluate a province's similar capabilities in producing an agricultural product related with its other products. In agricultural production space, if two agricultural products are related because they require similar climate, soil, water, technology, or some combination thereof, they are likely to be produced together in the same provinces. Metrics of proximity connect pairs of agricultural products or pairs of provinces. The proximity between the pairs of products  $k$  and  $\tilde{k}$  is the minimum probabilities of a province producing a specific product given that it produces another (Hidalgo, 2021). To analyze the evolution of productive structure, the APS is projected into "product space" and "province space" by defining their similarity with proximity matrix. Within the agricultural product space, each pair of nodes is linked with their degree of similarity. According to the Hidalgo (2021), the similarity  $N_{k\tilde{k}}$  is defined as follows:

$$M_i = \sum_k M_{ik} \quad (2)$$

$$M_k = \sum_i M_{ik} \quad (3)$$

$$N_{k\tilde{k}} = \sum_i \frac{M_{ik} M_{i\tilde{k}}}{M_i M_k} \quad (4)$$

where,  $M_i$  and  $M_k$  represent the number of products produced by that province, and the number of provinces producing a given products, respectively.  $N_{k\tilde{k}}$  is the similarity of the pairs of products  $k$  and  $\tilde{k}$ . Following the same strategy, an agricultural province space defined which nodes are provinces, and links between provinces  $i$  and  $\tilde{i}$  are weighted by  $N_{i\tilde{i}}$ :

$$N_{i\tilde{i}} = \sum_k \frac{M_{ik} M_{i\tilde{k}}}{M_i M_k} \quad (5)$$

where  $N_{i\tilde{i}}$  represent the similarity of the pairs of provinces  $i$  and  $\tilde{i}$ .

### 2.3.4. Core-periphery structure detection

The detection of core and periphery within the network can reveal localized network structures (Malliaros et al., 2020; Gallagher et al., 2021). Various methods and algorithms have been employed to extract network's core and periphery, such as statistical inference (Kojaku and Masuda, 2017; Peixoto, 2019), spectral decomposition (Cucuringu et al., 2016; Tudisco and Higham, 2019), diffusion mapping (Rossa et al., 2013) to motif counting (Ma et al., 2018), geodesic tracing (Cucuringu et al., 2016), and rich clubs (Ma and Mondragón, 2015). There is also a new approach to detect the core-periphery structure of weighted and undirected network. Unlike other methods determining whether a node belongs to core with "yes" or "no", this method uses a scoring system ranging between 0 and 1 to measure the degree of core.

A higher score indicates closer proximity to the core. Notably, a node is more likely in the network's core position which not only densely connects among other core nodes and has high strength, but also has links with peripheral nodes (Rombach et al., 2017). Moreover, core-periphery structure can also be nested with networks' community structure (Leskovec et al., 2009; Yang and Leskovec, 2012).

### 2.3.5. Community detection

Community detection may be a helpful tool for analyzing the differences of products group and provinces group. The traditional strategy of community detection focuses on optimizing modularity (Esfahlani et al., 2021), with example including Guimera's modularity (Guimera et al., 2007) and Barber's modularity (Barber, 2007). QuanBiMo is the first algorithm to maximize weighted modularity in bipartite network. However, its sensitivity to specific input variables that might not be accessible can lead to deviations from expected outcomes (Dormann and Strauss, 2014). Furthermore, DIRTLPawb+, an extension of QuanBiMo, performs well on small networks, which can search the optimal modularity in whole possible space (Beckett, 2016). In this study, the DIRTLPawb+ algorithm was used to maximize modularity scores in the networks. DIRTLPawb+ has more meaningful input parameters and exhibits enhanced performance. Its implementation is also more stable than that of QuanBiMo on the test (Beckett, 2016).

## 3. Results

### 3.1. Overview of the "province-product" agricultural production space

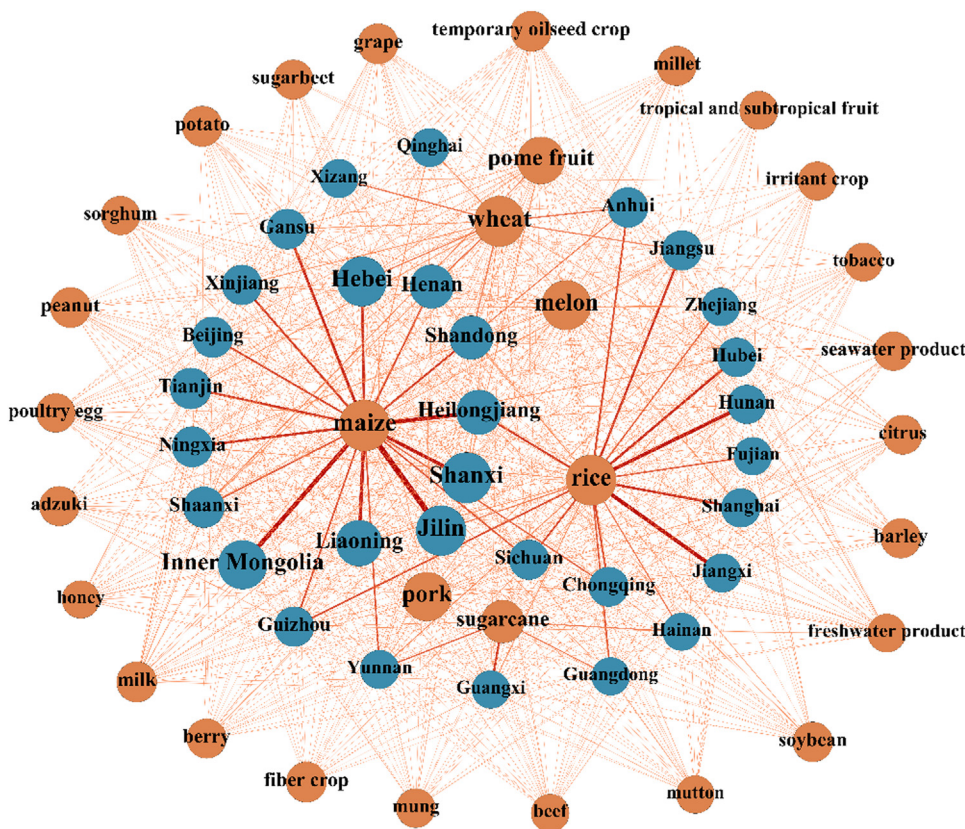
The "province-product" agricultural production space has been built to exhibit how provinces grow agricultural products from 1995 to 2019. Fig. 2 shows the case of 2019 and it clearly demonstrate that the network's central nodes include maize, wheat, rice, pork, sugarcane, pome fruit, and melon, indicating the critical role of these products in the food production system. Additionally, this network effectively depicts the geographical distribution of agricultural products across China. Maize predominantly links with provinces in the norther China, such as Hebei, Henan, Heilongjiang, Liaoning, Jilin, Shanxi, and the Inner Mongolia Autonomous Region. Meanwhile, rice exhibits strong connections with southern provinces like Anhui, Jiangsu, Jiangxi, Hunan, Hubei, Sichuan, and Guangdong. Similarly, wheat primarily connects with Henan, Shandong, Hebei, Shaanxi, and Anhui. These findings are well consistent with previous researches conducted by Ye et al. (2020), Bai et al. (2021), L. Zhang et al. (2022). Sugarcane, a typical tropical and subtropical product, is logically planted in Hainan, Guangdong, Guangxi, and Yunnan. Blue provincial nodes represent traditional agricultural production areas that have diverse products and higher output, which include Shandong, Henan, Hebei, Heilongjiang, Shanxi, Jilin, and Liaoning. In contrast, provinces like Qinghai, Hainan and Xizang Autonomous Region occupy a more peripheral position, in keeping with the actual state of agricultural production (Guo et al., 2020). The darker-colored links connecting maize, rice, wheat, melon, and pork to their provinces signify that these products have considerable importance in their provinces. Products located in the outer ring exhibit sparse and weaker links, likely due to their requirement for specialized production conditions, often connect to specific provinces within a limited geographic area. Our subsequent investigation will delve into the core-periphery structure and community structure within both the agricultural product space and the province space.

### 3.2. Analysis of the core-periphery structure

#### 3.2.1. Core-periphery structure of agricultural product space

Fig. 3(a) shows the bubble matrix diagram that illustrates the core score ranking of each product from 1995 to 2019. Among all products, maize, wheat and rice consistently maintain the highest position, with maize gradually surpassing wheat and rice, which there is no doubt that





**Fig. 2.** Agricultural production space in 2019.  
*Note:* Nodes are two disjoint sets that represent products and provinces. Product nodes are orange, and province nodes are blue. The size of the nodes represents their importance in the network. Links are color coded with their RCA value. Links are always between the node of the product set and a node of the province set, and there is not a link between two nodes in the same set. The darker color of links indicates the stronger capabilities of this province to produce a specific product.

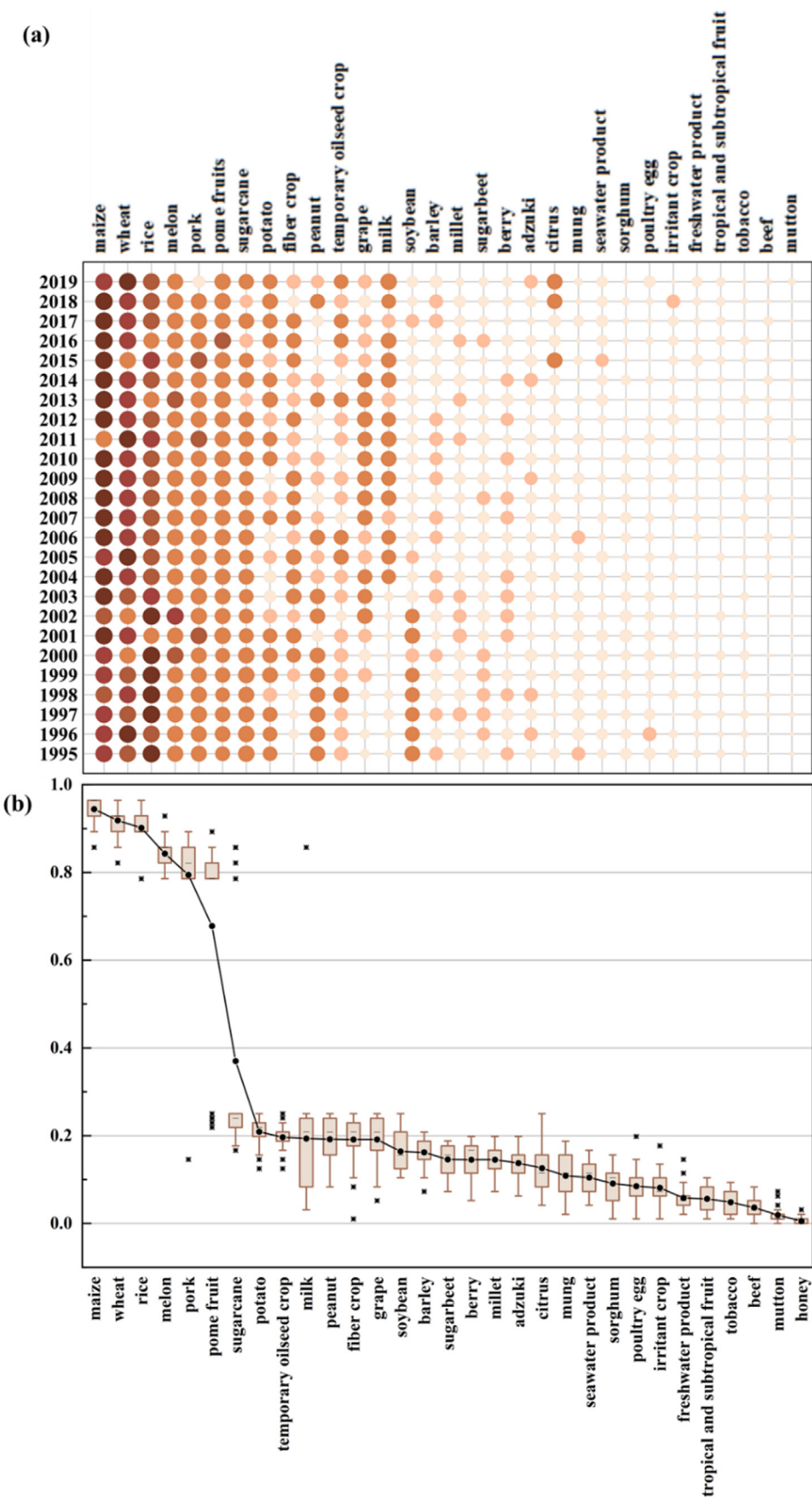
these three products dominate agricultural production in China. It is also worth noting that melon (watermelon and muskmelon), pork, and pome fruit (apple, pear, jujube, and persimmon) are in the fourth, fifth and sixth places, respectively. The core score of pork remained relatively stable from 1995 to 2018 but witnessed a sharp decline in 2019 due to the impact of the African swine fever and “Enhanced Pig Cycle” (EPC). This event led to a significant reduction in domestic pork production, plummeting from 54.075 million tons to 42.553 million tons (Song et al., 2022). Melon, as one of the most consumed food in China, experienced an expansion in its planting area from 1,013.52 ha in 1995 to 1,894.05 ha, representing approximating 40% of the global yield from China (Luo et al., 2018). Pome fruits, including apple, pear, jujube, persimmon, serve as necessary food in our daily diet. Their planting areas in China are concentrated in the northern provinces, maintaining stable growth in their output (Wang et al., 2020; Qi et al., 2023). For example, cultivation area of apple has expanded from semi humid (irrigated) to semi-arid (rain-fed) area (Zhang et al., 2023). Fiber crops (flaxseed, rapeseed, sesame, and sunflower) and grape have experienced a consistent increase in their ranking since 1999, while milk began to rise in 2004. On the contrary, oil crops (temporary oilseed crop, peanut, and soybean) displayed a declining trend until 2019. Other products with invisible color such as barley and mutton are usually away from the core area in the network except some extreme years. For example, citrus achieved relatively higher rankings in 2015, 2018, and 2019 compared to other years, mainly owing to a rapid surge in citrus output during these years (from 245.25 million tons to 274.01 million tons).

Fig. 3(b) shows the box diagram presenting the core score for each product from 1995 to 2019, offering a clearer understanding of the overall differences among agricultural products. The mean core scores for maize, wheat, and rice are 0.9443, 0.9187, and 0.9015, respectively. Following these, melon (0.8428), pork (0.7944), and pome fruit (0.67769) hold relatively high average core scores. These products, as highlighted by Wang et al. (2019), are fundamental foods in the

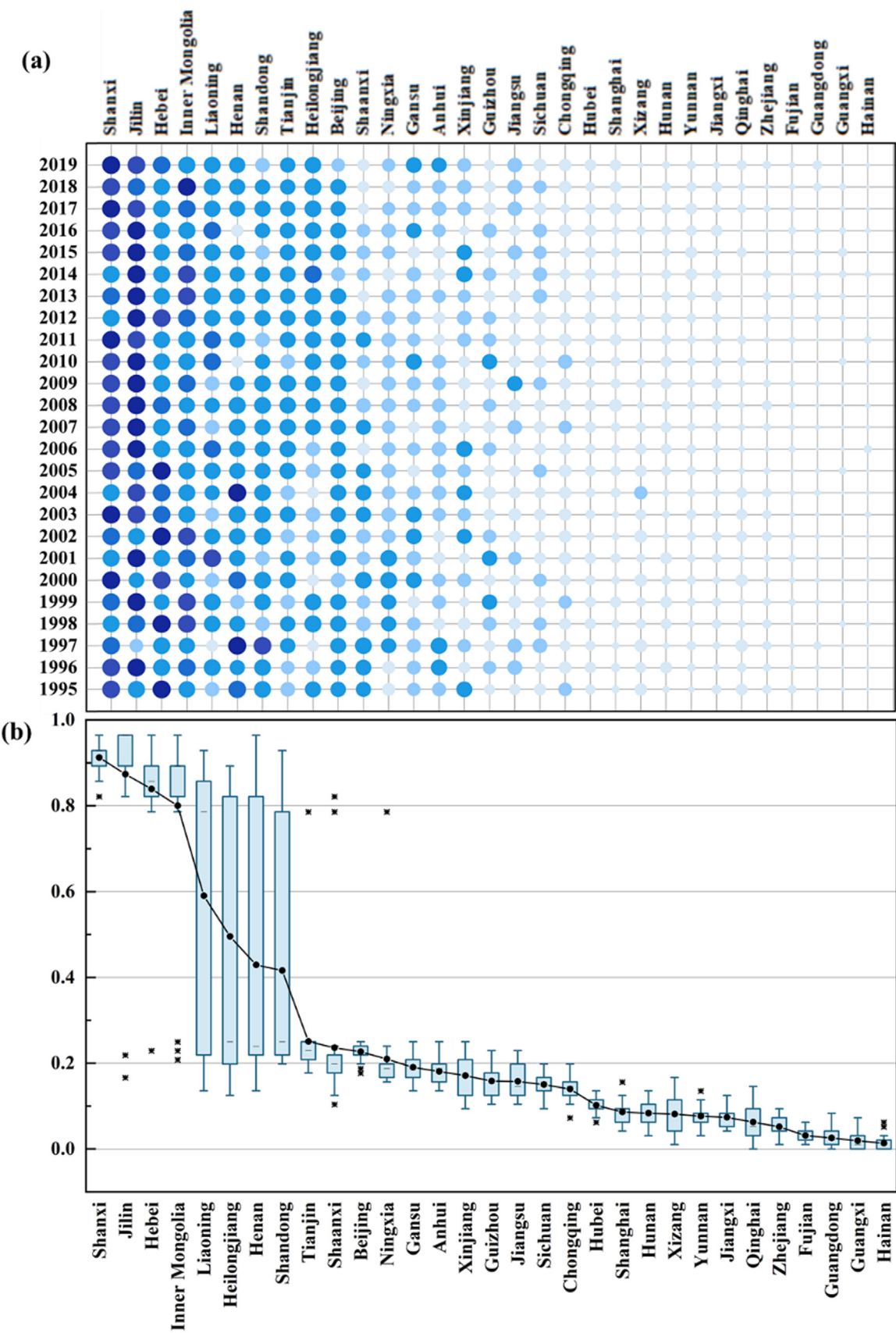
Chinese diet and are cultivated in relatively high-producing regions, which dominate Chinese food system. In the second order, with slightly lower core score compared to the first order, are agricultural products such as potato, temporary oilseed crop, milk, peanut, fiber crop, grape, and soybean. These products are still substantially important in our daily diet or living (Liu et al., 2021). Products limited to specific regions with specific conditions are positioned on the network’s periphery, with relatively lower scores. For instance, sugar beet, millet, adzuki, mung, and sorghum are mostly cultivated in northern China (Lin et al., 2023). Citrus, irritant crop, freshwater product, seawater product, tropical and subtropical fruit are mainly in south China (Duan et al., 2020; Yan et al., 2020). Tobacco has widespread distribution in southern hilly area (Liu et al., 2018). Beef, mutton, and honey are concentrated to produce in northwest China (H. Zhang et al., 2022).

### 3.2.2. Core-periphery structure of agricultural province space

As depicted in Fig. 4(a), provinces such as Shanxi, Jilin, Hebei, Inner Mongolia Autonomous Region, Liaoning, Heilongjiang, Henan, and Shandong occupy relatively higher rankings. These provinces exhibit high strength in main agricultural products, particularly in maize, wheat, rice and pome fruit. Additionally, these provinces are well-connected to each other or even to some peripheral provinces. For example, Shanxi not only share connection with Henan, Hebei, Shandong, Inner Mongolia Autonomous Region, but also demonstrate strong links with Gansu, Shaanxi due to their mutual cultivation of specific agricultural products. The main agricultural products of high-ranking provinces have been outlined in Table S1. Liaoning, Tianjin and Heilongjiang have demonstrated a gradual upward trend in their rankings. Conversely, Shaanxi, Ningxia, and Gansu show a decreasing trend. Anhui and Xinjiang Uygur Autonomous Region exhibit noticeable fluctuations. While provinces like Xizang Autonomous Region and Qinghai, situated on the Qingzang Plateau with limited cultivated land and lower temperature, maintain lower rankings. Hainan, Guangdong, and



**Fig. 3.** Core-periphery structure in agricultural product space. (a) The bubble matrix diagram of core score rankings of each product; (b) Box diagram of core scores from 1995 to 2019 for each product.  
*Note:* Dots with darker colors and wider sizes have higher core scores. The line in the box represents the median value, and the solid dot indicates the mean value, which is linked by a black solid line. The asterisk denotes the outliers. The two ends of the box are the first and third quartiles.



**Fig. 4.** Core-periphery structure in agricultural province space. (a) The bubble matrix diagram of core score rankings of each province; (b) Box diagram of core scores from 1995 to 2019 for each province.  
*Note:* Dots with darker colors and wider sizes have higher core scores. The line in the box represents the median value, and the solid dot indicates the mean value, which is linked by a black solid line. The asterisk denotes the outliers. The two ends of the box are the first and third quartiles.



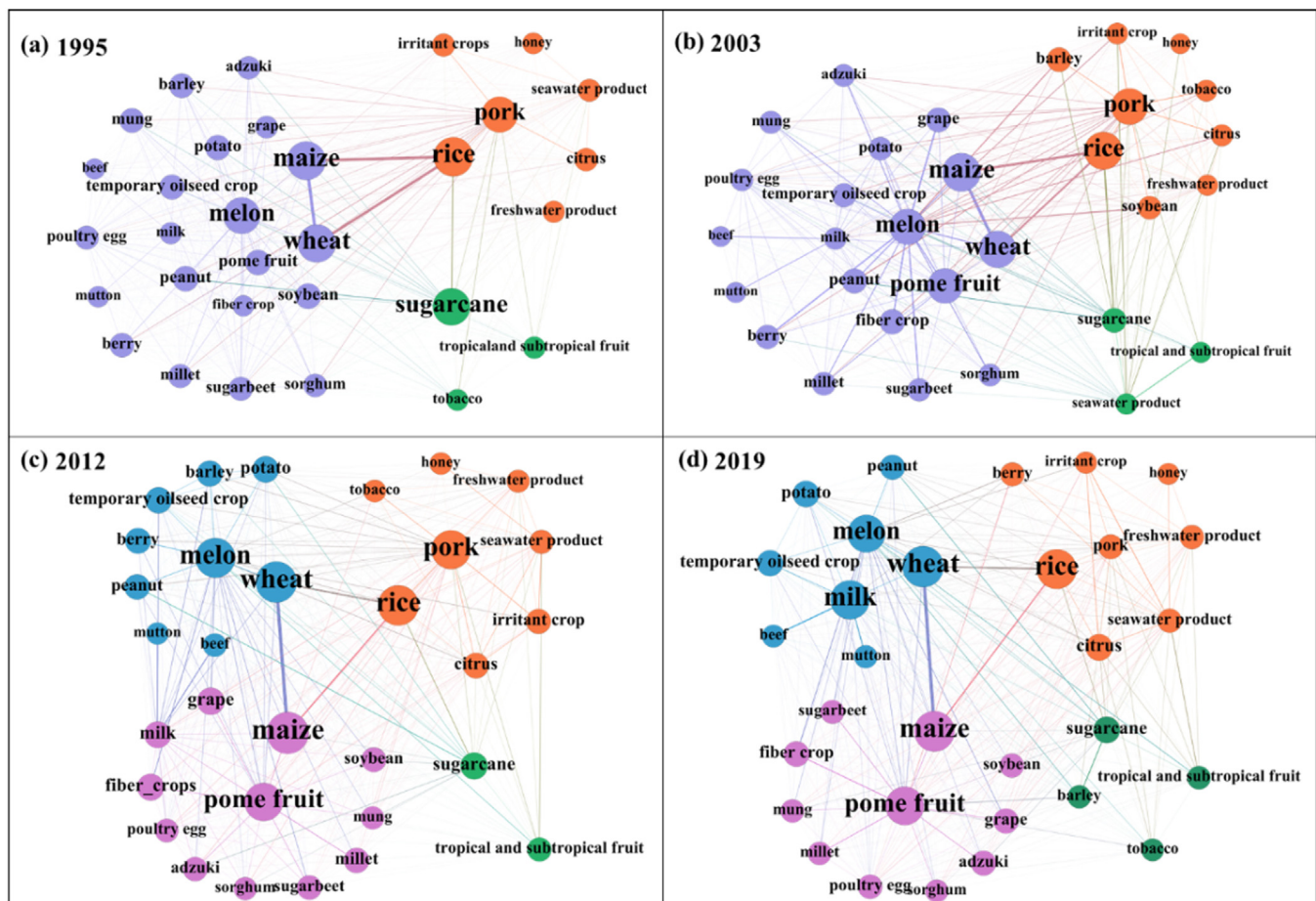


Fig. 5. Community presented in agricultural product space from 1995 to 2019.

Guangxi which primarily focus on tropical and subtropical products, have fewer connections to products of other provinces. Therefore, they are at the lower rankings of the network. The box diagram in Fig. 4(b) shows a clearer insight of each province's core score from 1995 to 2019. Shanxi, Jilin, Hebei, and Inner Mongolia are in the high positions, with average scores over 0.8. Following closely are Liaoning, Heilongjiang, Henan, and Shandong, with scores fluctuating between 0.1 to 1. Conversely, other provinces have scores that are approximately below 0.3, and in some case, nearly 0. Despite these relatively lower scores, these provinces still play vital roles in some specific products. For example, Fujian, Guizhou, and Yunnan are significant for tea production; Qinghai, Xinjiang Uygur Autonomous Region and Xizang Autonomous Region are important for mutton production (Yan et al., 2021).

### 3.3. Changes in the relatedness among agricultural products

The evolving relatedness among different agricultural products are investigated by community detection and the outcomes are presented within the agricultural product space. These communities gather products that share similar production conditions or capabilities. As shown in Fig. 5, the node size corresponds to the centrality of each product, determined by its core score. The modularity ranges from 0.4749 to 0.5957, which can support the possibility to present network substructures. A total of three to four communities are detected from 1995 to 2019. From 1995 to 2002 and from 2003 to 2011, the networks are divided into three communities. The purple community mainly includes maize, wheat, melon, pome fruit soybean, temporary oilseed crops and some peripheral products that are mainly suitable in north of China. The orange community is dominated by pork and rice, both of which

require more heat and water resources for their production compared to the products in the purple community. The green community includes sugarcane and tropical and subtropical products. The community compositions in 2003 resemble those in 1995, with the exception of soybean, which has moved to the orange community with pork and rice. Since 2012, four communities are detected, and this configuration remains relatively stable until 2019. Notably, maize and soybean are observed within the same community after 2012, while other communities exhibit minimal changes over these years.

The Sankey graph presented in Fig. 6 shows the dynamic changes in agricultural components over time, with core products highlighted in bold. The core products within each community remain almost unchanged from 1995 to 2019, suggesting a relatively stable network structure in this period. This finding implies product structure in China's agricultural production demonstrates a remarkable stability (Huang and Tian, 2019; Guo et al., 2020), in line with the actual situation of agricultural production in China, because production conditions such as soil, cropland, climate, cultivation habits are long-term elements and infrequent changes. Additional noteworthy finding is the transition from three communities during 1995 to 2003 to four communities after 2012. More importantly, soybean is separated from the rice and pork groups to the community with maize, milk, pome fruit, grape, and fiber crops until 2019. Furthermore, it is also important to point out that the position of barley frequently changes, influenced by fluctuations in output within its primary production regions. Barley output declines from 0.805 million tons to 0.239 million tons in Jiangsu, 0.123 million tons to 0.002 million tons in Zhejiang, 0.369 million tons to 0.109 million tons in Henan, 0.125 million tons to 0.0254 million tons in Hubei, and 0.546 million tons to 0.133 million tons in Gansu. However, an increase

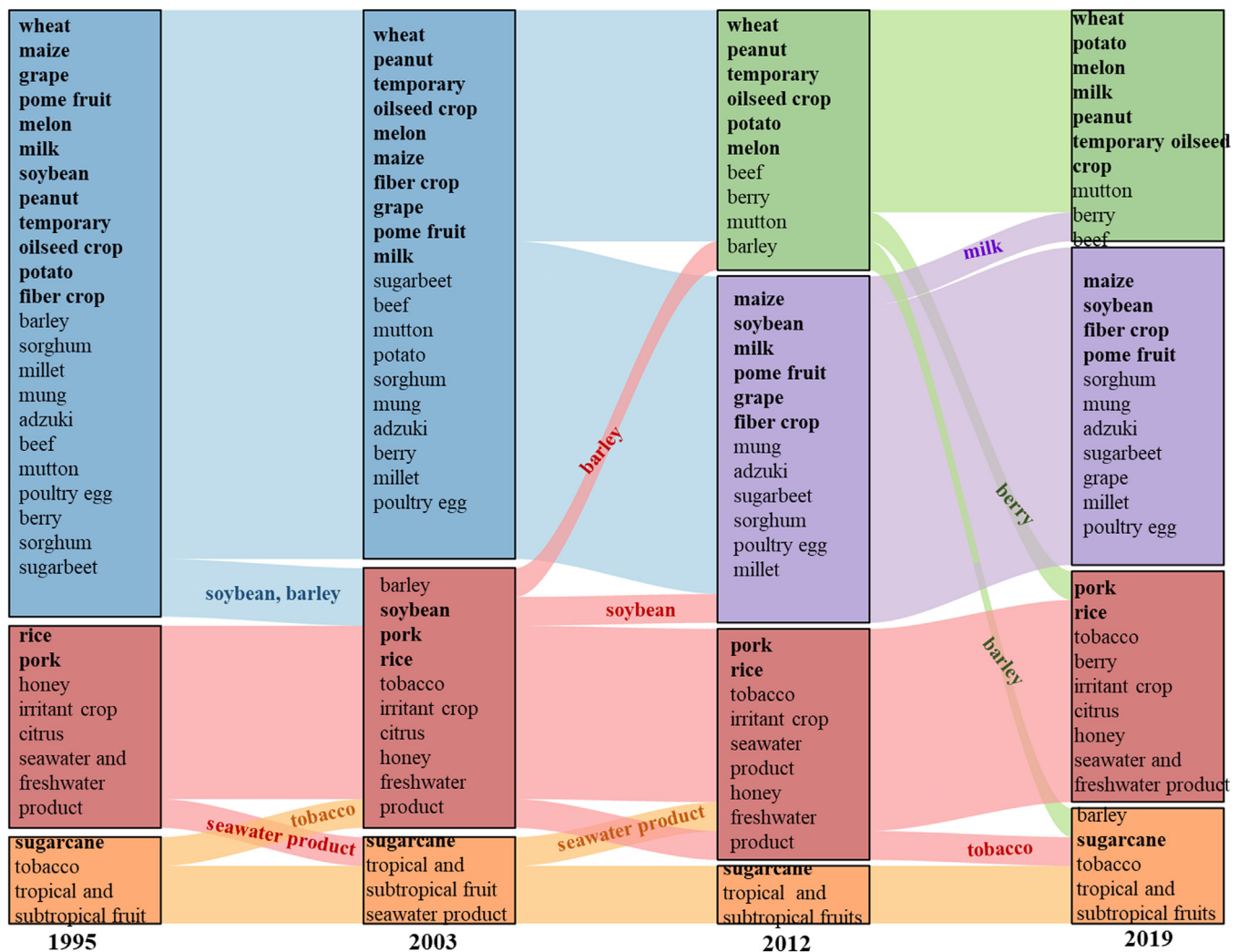


Fig. 6. Changes in community components.

is found from 0.135 million tons to 0.291 million tons only in Yunnan. As a result, barley moves to communities with sugarcane, tobacco, and tropical and subtropical fruits, as this community mainly corresponds to Yunnan, Guangxi, Guangdong, and Hainan. Changes in tobacco and seawater product between red and orange communities imply that products in these two communities possibly share similar production conditions.

### 3.4. Spatiotemporal characteristics of provincial production capabilities

Fig. 7 (a) shows the communities within the agricultural province space and China's agricultural natural zones in 2019. Three provincial communities are detected from 1995 to 2019. The nodes represent the centrality of each province within the network. The darker color of the line denotes a stronger connection between these two nodes, and linkage within a group is denser and stronger compared to those between groups. The findings reveal that Jilin, Liaoning, Heilongjiang, Hebei, Shanxi, and Shandong are in the center within the network. Interestingly, the composition of these communities within the province space remains unchanged during this period. Furthermore, three provincial communities closely resemble the geographical distribution of China's agricultural natural zones. The variation in heat in different zones significantly influence crop types, crop distribution, growing seasons and cropping systems (Table S2 for detailed information). Specifically, community A includes the provinces of North China, Northeast China, Northwest China, Qinghai and Xizang Autonomous Region, covering mid-

temperature zone, cold temperature zone, and warm temperature zones. Characterized by warm and rainy summers as well as cold and dry winters, the cultivation patterns of these provinces are mainly irrigated and dryland agriculture. The main agricultural products within them are maize, wheat, pome fruit, fiber crops, potatoes, melons, and temporary oil crops. Community B includes Jiangsu, Shanghai, Zhejiang, Sichuan, Chongqing, Guizhou, Jiangxi, Hunan, Hubei, and Fujian, situated in the middle and north subtropical zones. Finally, community C includes Guangdong, Guangxi, Yunnan, and Hainan, located in South China, mainly located in mid-tropical and south-tropical zones, which are well-suited for cultivating tropical and subtropical products such as sugarcane, tobacco, banana, and pineapple.

Fig. 7(b) shows the production capabilities of each province within three identified communities. Provinces within community A exhibit significant differences in production capabilities. Heilongjiang and Jilin, the top two provinces in community A, whose production capabilities reach 0.18 and 0.16, respectively, are higher than those of other provinces in the community. Conversely, Qinghai and Xizang Autonomous Region exhibit relatively lower production capabilities. Despite these differences, there exists a consistent trend in production capabilities among provinces in community A, which the average production capabilities decreased to 0.8 from 1995 to 2003 and then gradually increased in total. However, community B and C show different trends. In these communities, production capabilities have demonstrated a declining trend from 1995 to 2019. Production capabilities in community



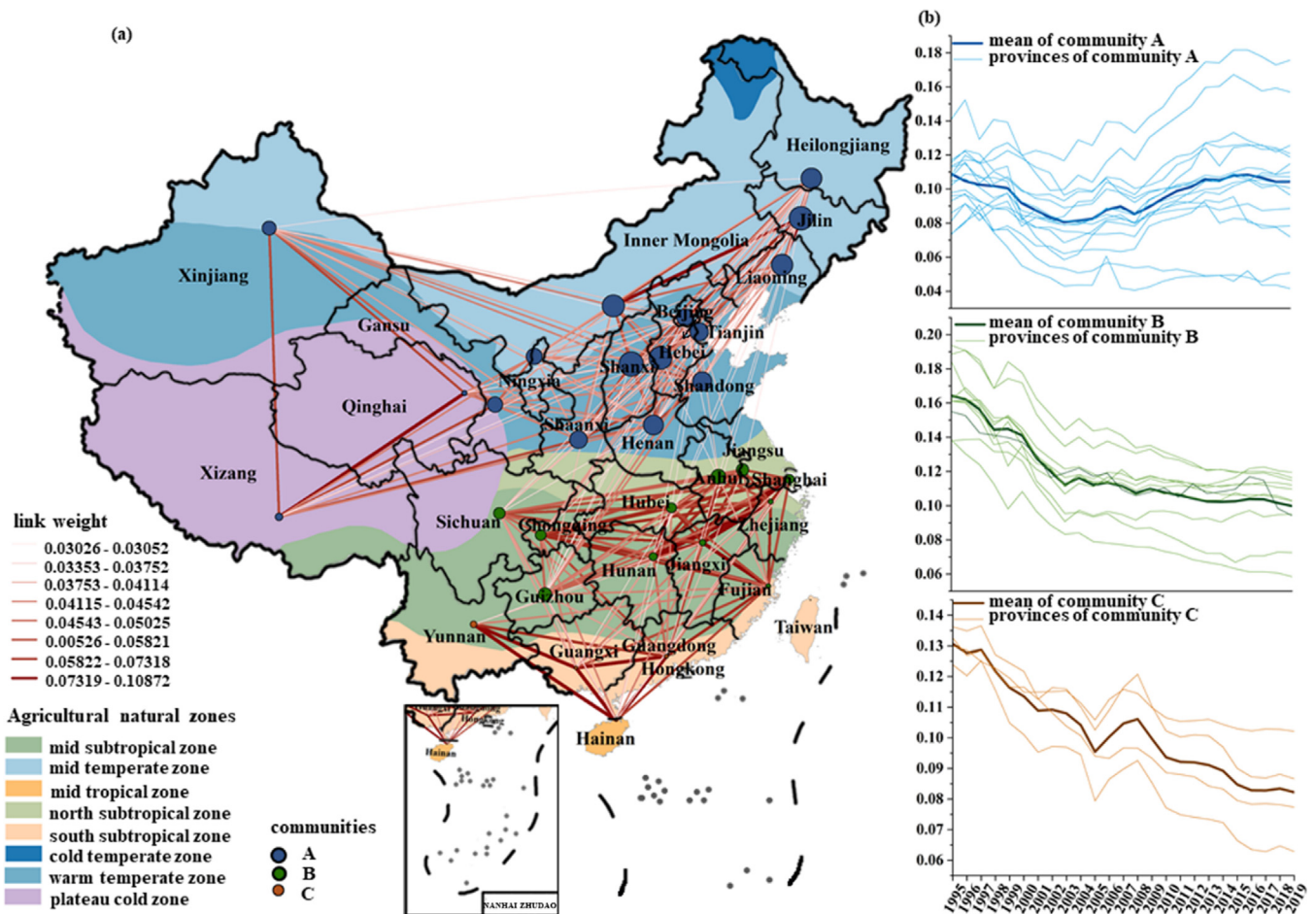


Fig. 7. (a) Communities and capabilities of the agricultural province space; (b) Changes in production capability in different communities and provinces.

Note: The node sizes are the average core value in each province from 1995 to 2019. The links represent the similarities between any pair of nodes. The average value in Fig. 7. (b) is highlighted in darker color.

B experienced a rapid drop, declining from nearly 0.18 to 0.12 by 2003, followed by a slight decline from 0.12 to 0.1 on average after 2003. Similarly, community C showed a consistent and steep decline in production capabilities, plummeting from 0.13 to 0.09 over the observed period. Despite the decreasing trend in production capabilities within communities B and C, the majority of provincial capabilities still remain higher compared to those within community A.

## 4. Discussion

### 4.1. Impact of consumption trends on agricultural products

With the growing income of urban and rural residents and the improving living standards, the dietary structures and food consumption of residents are upgrading (Yang and Cui, 2023). Diet becomes healthier and more diverse. This shift is characterized by a gradual decrease in the consumption of staple foods, and an increasing demand for animal-derived foods, milk, vegetables, melons, fruits and fiber crops (Zhao et al., 2018; He et al., 2020; Xin, 2021). Our aforementioned findings on changes in centrality of agricultural products can illustrate this point, such as the decreasing centrality of rice and wheat, and the increasing importance of milk, fruit, and fiber crop during 1995–2019. Moreover, it is crucial to note that agricultural production is highly related with consumption trends. Taking the example of maize, its increasing centrality is attributed not only to its high output and extensive planted areas, but also to its substantial demand in livestock production. Maize is a vital raw material and component of animal feed, with its

share in feed consumption surpassing that in human food consumption (Ranum et al., 2014; Yang and Cui, 2023). The surge in meat consumption has also heightened demand for feed grains, making them a “rigid demand” (Dong et al., 2015; Zhao et al., 2021). There is no doubt that rice, wheat and maize are constantly in the core of China’s agricultural production and main determinants of food security, with their sowing areas accounting for 81% of country’s grain sowing area (Fig. S3). As for some peripheral products such as subtropical fruits, honey, millet and barley, although they might not be widely distributed and planted across China, they still hold vital significant parts within the national food production and residents’ consumption.

### 4.2. Relationship between diversifying agricultural product bundles and production capability

The findings show that provinces concentrate their production on products that require similar environmental conditions and capabilities. Although provinces have the potential to diversify their production across numerous products, the distribution of product bundles remains uneven among provinces. In fact, specific provinces tend to dominate certain products (Zou et al., 2020). If only natural conditions are taken into account, provinces would diversify their product bundles based on their inherent and similar natural advantages (Gao and Zhou, 2018). In this study, the production patterns within agricultural product space closely related with the natural conditions. For instance, agricultural production in community with maize, wheat, melon, and pome fruit likely need relatively lower temperature in China; products

in community with rice, pork, and citrus may necessitate warmer and more humid climatic conditions; the communities with sugarcane, tropical and subtropical fruits is shaped by high temperature and abundant water resource. These results are coincided with previous studies by Yu et al. (2022), Yao et al. (2022) and Guga et al. (2021). Moreover, compositions of these communities are relatively stable. On the one hand, this stability suggests that provinces much possibly concentrate on specific products for long time, as not all provinces possess the natural conditions to produce all type of agricultural products. On the other hand, the fundamental natural conditions required for agricultural production, such as soil, climate, and water resource, do not frequently change (Maja and Ayano, 2021). Diversifying agricultural product bundles is a long-term process and needs a considerable amount of time. Therefore, notable changes in product patterns might not be observed in short time.

#### 4.3. Impact of national policies on spatiotemporal changes in production capability

We observe that production capabilities are unevenly distributed and that they shape different characteristics in province space. From the changes of provincial capabilities, the North and Northeast China have an upward trend in production capabilities, gradually becoming a new focus area of agricultural production in China (Xin et al., 2020), which agrees with the study that the agricultural production center is moving north (Lu et al., 2020; Liu and Zhou, 2021). Additionally, the differences between provincial capabilities also need to be noted within each community. Within community A, provinces like Shandong, Henan, Heilongjiang, Liaoning, Jilin, Hebei are showing a growing trend in production capabilities. Because these provinces are located in traditional agricultural production regions (Ma et al., 2021), hereby possibly receiving many policy, technology, and infrastructure supports (H. Chen et al., 2022; Y. Liu et al., 2022). Taking the Northeast China Plain and the Huang-Huai-Hai Region as an example (Ren et al., 2021), it has been designated as functional production zones for rice, wheat, maize and protected production zones for soybean in the 14th Five-Year Plan for Promote Agricultural and Rural Modernization. On the contrary, the production capabilities of Gansu, Shaanxi, and Ningxia grows relatively slowly, because these provinces are located in the semi-arid and arid regions in northwest China with vulnerable ecosystem environment and scarce water resources (Gao et al., 2022). Northwestern provinces prioritize ecological security and ecosystem sustainability rather than fully develop agriculture production. For example, vigorous implementation of China National Project to Returning Farmland to Forest and Grassland in northwest China (W. Li et al., 2020) possibly leads to a decrease in farmland in some areas (Qu et al., 2022). For instance, forested areas in Ningxia expanded from 514,000 ha in 1985 to 2,202,000 ha in 2015 (Z. Li et al., 2020); abundant unsuitable cropland turned into grassland and forest in the Loess Plateau, where afforestation area reached 18.906 million ha in 2018 (Gu et al., 2021). Communities B and C, including southern and eastern provinces, aim at economic development in China and have become a demand side of agricultural products (Li et al., 2021). Although provinces in south China still exhibit remarkable superiority in agricultural production, their production capabilities have obviously declined. With the changes in economic development, production capabilities, food supply and demand, agricultural production patterns also need to adapt to these changes. The natural and climatic conditions, consumption preferences, natural zone and human zone plans are highly heterogeneous within regions and provinces, offering opportunities for shaping and diversifying different agricultural production patterns (Guo et al., 2023).

#### 4.4. Policy implications

Maintaining and improving higher agricultural production capabilities are crucial to ensure future food security and achieve food system

sustainability in China, particularly in high-standard farmland. The recent 14th National five-year-plan also has emphasized importance of enhancing food production capabilities (He et al., 2022). To this end, the formulation of high-standard farmland and functional agricultural production zone should consider the spatiotemporal changes in local agricultural production capabilities. In recent years, huge changes have taken place in the major agricultural production zones due to the rapid urbanization and human activities (Jin et al., 2020), where it is essential to implement rational spatial planning and ensure a certain amount of high-yield farmland. Spatial match of natural resources and production capabilities is helpful to optimize agricultural production layout and improve food supply.

Diversifying agricultural product bundles should not only consider the production capability required, but also take the relatedness among agricultural products into account. This is because there are various challenges that a region shifts to produce a new product far away the scope of its existing agricultural product space. Taking mixed crop-livestock farming as an explanation, soybean is closely related with pork production. On the one hand, the closer producing areas can efficiently save cost of feed transportation. On the other hand, pig manure can be used as fertilizer for soybeans. Furthermore, soybean and pork are in the same community and may require similar production conditions and capabilities. Diversified multi-cropping system with high productivity and low environmental costs is regarded as an effective way to improve the spatial match of natural resources and sustainable agriculture development (Xian et al., 2023).

Overall, the agricultural production space shows how provinces use their capabilities to shape agricultural production, providing a better understanding to upgrade and diversify agricultural product bundles. The success of provinces diversifying their products depends not only on geographical and social factors, but also on the knowledge and technological capabilities between new products and provinces' existing and accumulated capabilities (Boschma, 2005). The dynamic evolution of China's agricultural product space and province space is a self-adjustment process within food system in response to natural conditions, consumption trends and policies, which not only reflects the changes in China's agricultural production structures, but also helpfully improves the spatial match of agricultural production resources (Davis et al., 2017).

#### 4.5. Limitations

Nevertheless, it's important to acknowledge the limitations of this study. Firstly, the spatiotemporal characteristics and specialization patterns of specific products inside specific provinces have not been studied, which is very important for regional agricultural planning and should be investigated in the future. Furthermore, due to data constraints, this study is based on Level 2 products at the province scale. With higher resolution data, more detailed and fuller network structures might be identified and would reveal more accurate agricultural production space, structure and patterns. Finally, while our work shows the effectiveness of bipartite network in spatial heterogeneity and evolution analysis (Zaccaria et al., 2014; Cristelli et al., 2015), it is essential to recognize other methods for network analysis (e.g. multinet network analysis) could be considered in future research (Battiston et al., 2017; Torreggiani et al., 2018).

#### 5. Conclusions

In this study, we apply complex network approach to build China's agricultural production space, and then project it into agricultural product space and province space with proximity matrix. Both product space and province spaces exhibit distinct core-periphery structures and well-defined community structures. In the core-periphery structure, the changes in centrality of agricultural products are affected not only by natural conditions, but also residents' dietary preference and consumption changes. In the agricultural product space, production conditions



required for agricultural products within each community are relatively close, which is in line with the detection principles of similar capabilities. Additionally, the compositions of communities do not frequently change over time, indicating a relatively stable pattern in China's agricultural production. In the province space, three communities characterize with similar endowments of capabilities for agricultural production and highly resemble agricultural natural zones. Furthermore, there has been a general upward trend in production capabilities in North and Northeast China. Although production capabilities in southern provinces are declining, they still exhibit remarkable superiority in agricultural production. The changes and differences of capabilities among provinces also deserve our attention, which is helpful for understanding the possibility and pathway to diversify agricultural product bundles. This study provides a holistic perspective to understand the complex relationship of production capabilities, production space and structure of China's agricultural system, giving reference for agricultural sustainable development.

### Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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### Supplementary materials

Supplementary material associated with this article can be found, in the online version, at [doi:10.1016/j.geosus.2023.11.007](https://doi.org/10.1016/j.geosus.2023.11.007).

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