International Journal of Geo-Information

MDPI

*Article*

# New Insight into the Coupled Grain–Disaster–Economy System Based on a Multilayer Network: An Empirical Study in China

**Hongjiao Qu [1], Junli Li [1,2,*], Weiyin Wang [2], Wenwen Xin [2], Cheng Zhou [2] and Zongyi He [3]**

[1] College of Resources and Environment, Anhui Agricultural University, Hefei 230036, China; 872164393@stu.ahau.edu.cn
[2] Key Laboratory of JiangHuai Arable Land Resources Protection and Eco-restoration, Anhui Agricultural University, Hefei 230036, China; 20720673@stu.ahau.edu.cn (W.W.); 2277571039@stu.ahau.edu.cn (W.X.); 20721664@stu.ahau.edu.cn (C.Z.)
[3] School of Resource and Environmental Sciences, Wuhan University, 129 Luoyu Road, Wuhan 430079, China; 00200385@whu.edu.cn
* Correspondence: lijunli866@whu.edu.cn

**Abstract:** Natural disasters occur frequently causing huge economic losses and reduced grain production. Therefore, it is important to thoroughly explore the spatial correlations between grain, disaster, and the economy. Based on inter-provincial panel data in China in 2019, this study integrates complex network and co-occurrence theory into a coupled grain–disaster–economy (GDE) multilayer network, which provides a new perspective to further explore the spatial correlation between these three systems. We identify the spatial coupled characteristics of the GDE multilayer network using three aspects: degree, centrality, and community detection. The research results show the following: (1) Provinces in the major grain-producing regions have a stronger role in allocating and controlling grain resources, and the correlation between grain and disasters in these provinces is stronger and more prone to disasters. Whereas provinces in the Beijing–Tianjin–Hebei economic zone, and the Yangtze River Delta and Pearl River Delta economic zones, such as Beijing, Tianjin, Jiangsu, Shanghai, and Zhejiang, have a high level of economic development, thereby a stronger ability to allocate economic resources. (2) The economic subsystem assumes a more important, central role compared with the grain and disaster subsystems in the formation and development of the coupled GDE multilayer network, with a stronger coordination for the co-development between the complex grain, disaster, and economy systems in the nodal provinces of the network. (3) The community modularity of the coupled GDE multilayer network is significantly higher than that of the three single-layer networks, indicating a more reasonable community division after coupling the three subsystems. The identification of the spatial characteristics of GDE using multilayer network analysis offers a new perspective on taking various measures to improve the joint sustainable development of grain, disaster, and the economy in different regions of China according to local conditions.

**Keywords:** grain–disaster–economy coupled system; multilayer network; co-occurrence; community detection

check for updates

**Citation:** Qu, H.; Li, J.; Wang, W.; Xin, W.; Zhou, C.; He, Z. New Insight into the Coupled Grain–Disaster –Economy System Based on a Multilayer Network: An Empirical Study in China. *ISPRS Int. J. Geo-Inf.* **2022**, *11*, 59. https://doi.org/10.3390/ijgi11010059

Academic Editor: Wolfgang Kainz

Received: 29 November 2021
Accepted: 12 January 2022
Published: 13 January 2022

**Publisher's Note:** MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.

**Copyright:** © 2022 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/licenses/by/4.0/).

## 1. Introduction

China is a major agricultural country, and its food resources provide the material basis for regional economic development [1]. Ensuring food security is related to national livelihood and social stability [2]. Increasingly, global resource deprivation issues, food security [3], and persistent imbalances in regional economic development [4] have created barriers that restrict the development of modern society and seriously threaten national stability. With the increasing trend in global warming, China is being seriously affected by natural disasters [5–7]. Their frequent occurrence has brought serious challenges to the sustainable development of society [8]. The spatial network nexus of resources are network-type linkages that are gradually formed due to the flow and interaction of production

factors and outputs in geographic space [9,10]. These complex, global systems are all interconnected. Therefore, an intricate and interactive grain–disaster–economy (GDE) relationship, or nexus, can also be observed, that is, the production and supply of any one of the GDE components are dependent on those of the other two [11]. As the second largest economy, and one of the biggest resource consumers worldwide, China warrants further study with regards to the GDE nexus.

The nexus arises from increasing concern about the synergy of scarce resources through the internal links among sectors [12]. Many studies have focused on one or two elements of GDE. The frequent occurrence of natural disasters has a negative impact on the region [13], triggering a chain of losses and increasing socioeconomic vulnerability [14]. Consequently, a growing number of studies have focused on the impact of natural disasters on regional economies. Florida in the United States experienced a decline in income of up to 17% in the six months following a hurricane strike [15] and a significant decline in per capita income with successive major natural disasters [16]. Natural disasters can adversely affect production in the primary sector, leading to a sudden reduction in market production materials and directly affecting other various sectors [17]. The agricultural sector is most affected by climate-induced disasters [18]. Moreover, natural disasters are the main threat to the sustainability of grain production [19]. Droughts and floods significantly reduce grain production, and there is significant spatial variability in drought sensitivity [20]. The fuzzy relationship between the annual drought exposure rate and grain production losses due to drought provides important information for the development of disaster compensation plans [21]. Economy and ecology are key factors affecting the regional resilience index [22]. Economic development contributes the most to the reduction of disaster losses [23], meaning that rapid economic and technological development can, to some extent, resist or mitigate natural disasters [24]. In Ethiopia, policy evolution and recent changes that have led to significant progress in addressing grain insecurity are assessed, and the implications and lessons for other developing countries are discussed [25]. As a typical agricultural country, for the sustainable development of China's agricultural economy and grain security, the government should invest more funds in disaster prevention and mitigation, strengthen scientific and technological research, adjust the agricultural structure, improve the effective use of agricultural resources and the grain distribution system, balance the grain demand between grain use and indirect use, and achieve grain self-sufficiency and overall grain security [26,27]. The above studies mainly focus on the interaction mechanism, methodological diversification, and influencing factors between grain, disaster, and the economy, but few studies have analyzed their integration from a systemic perspective with a coupled multilayer coordination; therefore, it is important to explore the spatial association and coupled relationship between grain, disaster, and economy.

In order to understand the GDE nexus from a system perspective, and more deeply investigate the connections, functions, and interactions of grain, disaster, and economy systems, a complex network is introduced in this paper. Due to its unique strength in describing the interactions between the elements of complex systems [28], the complex network has received increasing research attention [29,30]. However, the complex network is unable to express the association of one subsystem with another in a complex system. In contrast, the multilayer network can clarify the overall and local interactions among multiple systems and reveal the spatial linkages between grain, disaster, and the economy. Furthermore, with the continuous development of network science, attention has shifted from single, isolated networks to coupled or multilayer interactive networks [31]. A multilayer network combines single-layer networks into a mathematical object by considering the interactions and impacts among different layers. The construction of multilayer networks can contain significantly more information and illustrate the relationship more accurately than single layers. Therefore, multilayer networks have become a research focus in the domain of complex networks [32]. In the current research, multilayer networks have been used in several academic fields. Examples include the financial stock market [33], transportation systems [34], and national energy trade [35]. The complexity of many bio-

logical, social, and technological systems stems from the richness of the interactions among their units [36]. Higher-order interactions have had a significant impact on the study of the dynamics of network systems, breaking the limitations of the original single type of pairwise interaction for network topology analysis and providing a new way of thinking for the interaction analysis of complex networks [37]. What is more, to date, no study has attempted to analyze the spatial nexus from the multilayer network perspective, and some challenges related to the application of the multilayer network remain due to the differences in the characteristics of the main networks. To address these issues, co-occurrence theory is introduced to deepen our understanding of the nexus effect. Co-occurrence analysis is the quantitative study of co-occurrence to reveal the content association of information and the knowledge implied by the feature items [38]. With the strengthening of interdisciplinary links and the penetration of academic research disciplines, co-occurrence analysis has been extended and applied to various disciplines, expanding the research space for its development [39–43].

Integrating the complex network and co-occurrence theory into the multilayer network to reveal the GDE nexus in an entire complex system can provide additional insights into grain and economy resource allocation over spatial regions. That is, a GDE multilayer network is constructed to explore the correlation and characteristics between single networks in a complex system. Based on existing research and the innovation point of this paper, we propose the following research hypothesis. (1) A gravitational model is used to construct a single complex grain, disaster, and economy network, which will effectively address the unevenness of the existing connection capacity and strength. (2) Integrating co-occurrence theory into the multilayer network will compensate for the shortcomings of a complex network approach and further explore the interlayer relationships among the single layers of the grain, disaster, and economy networks. (3) The construction of a coupled GDE multilayer network can not only achieve better spatial flow and the deployment of grain and economy resources but also obtain a more reasonable partition of a coupled GDE system based on the existing grain and economic partitions. It can also propose relevant measures to improve the joint sustainable development of grain, disaster, and the economy in different regions of China according to local conditions.

## 2. Methods and Data

### *2.1. Data*

Due to the lack of data availability, Hong Kong, Macao, and Taiwan were not included in the statistical analysis. By measuring the indicators of centrality characteristics from 2000 to 2019, it was found that there was no significant change in the provincial indicators for the grain single-layer network, and no significant shift in their relative positions in the correlation network. To maintain the consistency of grain, disaster, and economy indicators, we chose 2019 for the spatial coupled correlation characterization analysis of the GDE multilayer network. In the gravity model, the grain data includes grain production and the areas sown for grain crops [10], the disaster data includes the areas affected by all disasters as well as the areas of crop failure [44], and the economic data includes per capita GDP and per capita disposable income [3]. All the above data are from the "China Statistical Yearbook", the "China Rural Statistical Yearbook", and annual provincial data from the National Bureau of Statistics website. Details of all data can be found in Table 1.

By administrative region, China is divided into East China (EC), South China (SC), Central China (CC), North China (NC), Northwest China (NWC), Southwest China (SWC), Northeast China (NEC), Taiwan, Hong Kong, and Macao. The specific divisions are listed in Table 2 and Figure 1.

**Table 1.** The summary table of the data relating to the gravity model.

| Type | Variable | Variable Declaration | Source |
|---|---|---|---|
| Grain | Grain production | Used to characterize grain levels by region | China Rural Statistical Yearbook (2019) |
| | Areas sown for grain crops | | China Rural Statistical Yearbook (2019) |
| Disaster | Affected area | Used to characterize disaster levels by region | China Rural Statistical Yearbook (2019), the National Bureau of Statistics website |
| | Failure area | | China Rural Statistical Yearbook (2019), the National Bureau of Statistics website |
| Economy | Per capita GDP | Used to characterize economy levels by region | China Statistical Yearbook (2019) |
| | Per capita disposable income | | China Statistical Yearbook (2019), the National Bureau of Statistics website |

**Table 2.** Geographical information of seven administrative regions in China.

| Region | Area |
|---|---|
| North China | Beijing, Tianjin, Shanxi, Hebei, Inner Mongolia |
| South China | Guangdong, Guangxi, Hainan |
| East China | Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong |
| Central China | Henan, Hubei, Hunan |
| Southwest China | Chongqing, Sichuan, Guizhou, Yunnan, Tibet |
| Northwest China | Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang |
| Northeast China | Liaoning, Jilin, Heilongjiang |




**Figure 1.** Administrative and geographical divisions of China.

### 2.2. Multilayer Network

A multilayer network with $M$ layers [45] consists of a collection of different network layers $g$ and interlayer connected edges $c$. Here, $g = \{G_\alpha;\ \alpha \in \{1, \ldots, M\}\}$, $G_\alpha = (X_\alpha, E_\alpha)$, which is the network layer or layers of a multilayer network, and $c = \left\{E_{\alpha\beta} \in X_\alpha \times X_\beta; \alpha,\ \beta \in \{1, \ldots,\ M\},\ \alpha \neq \beta\right\}$, which is the set of connected edges between nodes of different network layers $G_\alpha$ and $G_\beta$. The constituent elements in $c$ are called cross layers, and the constituent elements of each $E_\alpha$ are called connected edges within a multilayer network layer, as distinguished from the constituent elements of each $E_{\alpha\beta}$ (i.e., connected edges between multilayer network layers). The superscript and subscript of the Greek letters are used to represent the indicators of the network layers. The set of nodes in the $G_\alpha$ layer is represented as $X_\alpha = \left\{X_1^\alpha, \ldots, X_{N_\alpha}^\alpha\right\}$. The adjacency matrix of each layer $G_\alpha$ is represented as $A^{[\alpha]} = \left(a_{ij}^\alpha\right) \in R^{N_\alpha \times N_\alpha}$. The interlayer adjacency matrix corresponding to $E_{\alpha\beta}$ is $A^{[\alpha,\beta]} = \left(a_{ij}^\alpha\right) \in R^{N_\alpha \times N_\beta}$.

$$a_{ij}^\alpha = \begin{cases} 1,\ if\ \left(x_i^\alpha, x_j^\alpha\right) \in E_\alpha \\ 0,\ otherwise \end{cases} \quad (1 \leq i,\ j \leq N_\alpha,\ 1 \leq \alpha \leq M) \tag{1}$$

$$a_{ij}^{\alpha\beta} = \begin{cases} 1,\ if\ \left(x_i^\alpha,\ x_j^\beta\right) \in E_{\alpha\beta} \\ 0,\ otherwise \end{cases} \tag{2}$$

### 2.3. Constructing the Grain–Disaster–Economy Multilayer Network

#### 2.3.1. Gravity Model

The GDE multilayer network is composed of three layers. Each layer consists of nodes and lines, with each province being a network node and the grain, disaster, and economy relationship between the provinces being the lines. Stewart [46] first proposed the gravity model (Equation (3)), which has been employed in recent years for spatial correlation analysis. In this study, a gravity model was applied to each network layer.

$$F_{ij} = K\frac{M_i M_j}{D_{ij}^2} \tag{3}$$

$$D_{ij} = \sqrt{R_{ij} T_{ij}} \tag{4}$$

where $F_{ij}$ represents the gravitational value between regions $i$ and $j$, $K$ is the gravitation coefficient, and $M_i$ and $M_j$ are the grain, disaster, and economy relationships scale of regions $i$ and $j$, respectively. $D_{ij}$ represents the distance between the centers of regions $i$ and $j$. Geographic distance and time costs are also introduced in this study. $R_{ij}$ represents the geographical distance and $T_{ij}$ represents the time cost.

The gravity model was modified based on previous studies [10], as shown in Table 3. In Table 3, we use indicators corresponding to grain, disaster, and the economy to modify the coefficient $K$ in the gravity model and characterize their levels in each province.

#### 2.3.2. Co-Occurrence Theory

Let a network layer set be $\{G_1, G_2, \cdots, G_L\}$, which interacts with each other, then they can be constructed as a multilayer network model (i.e., $\{G_1, G_2, \cdots, G_L\}$), where the cross layer $E_{\alpha\beta}$ corresponds to the interaction between network layers $G_\alpha$ and $G_\beta$ [47]. Figure 2a shows two networks with interactions, where the interactions can be represented by connecting edge arrows between the nodes in the layers, and Figure 2b shows the structure of a multilayer network consisting of these two interacting networks [45].

**Table 3.** Explanation of equation measurement for single-layer network.

| Layer | Network | Equation | | Description of Parameters |
|---|---|---|---|---|
| 1 | Grain correlation network | $G_{ij} = K1_{ij}\frac{\sqrt{G_iA_i}\sqrt{G_jA_j}}{D_{ij}^2}$<br>$K1_{ij} = \frac{G_i}{(G_i+G_j)}$ | (5)<br>(6) | $G_{ij}$ represents the gravitational value of the grain between regions $i$ and $j$, $G_i$ and $G_j$ are the grain production of regions $i$ and $j$, and $A_i$ and $A_j$ are the areas sown for grain crops of regions $i$ and $j$. |
| 2 | Disaster correlation network | $D_{ij} = K2_{ij}\frac{\sqrt{M_iN_i}\sqrt{M_jN_j}}{D_{ij}^2}$<br>$K2_{ij} = \frac{M_i}{(M_i+M_j)}$ | (7)<br>(8) | $D_{ij}$ represents the gravitational value of the disaster between regions $i$ and $j$, $M_i$ and $M_j$ are the affected area of regions $i$ and $j$, and $N_j$ and $N_j$ are the failure areas of regions $i$ and $j$. |
| 3 | Economy correlation network | $E_{ij} = K3_{ij}\frac{\sqrt{P_iI_i}\sqrt{P_jI_j}}{D_{ij}^2}$<br>$K3_{ij} = \frac{P_i}{(P_i+P_j)}$ | (9)<br>(10) | $E_{ij}$ represents the gravitational value of the economy between regions $i$ and $j$, $P_i$ and $P_j$ are the GDP per capita of regions $i$ and $j$, and $N_i$ and $N_j$ are the comp of regions $i$ and $j$. |

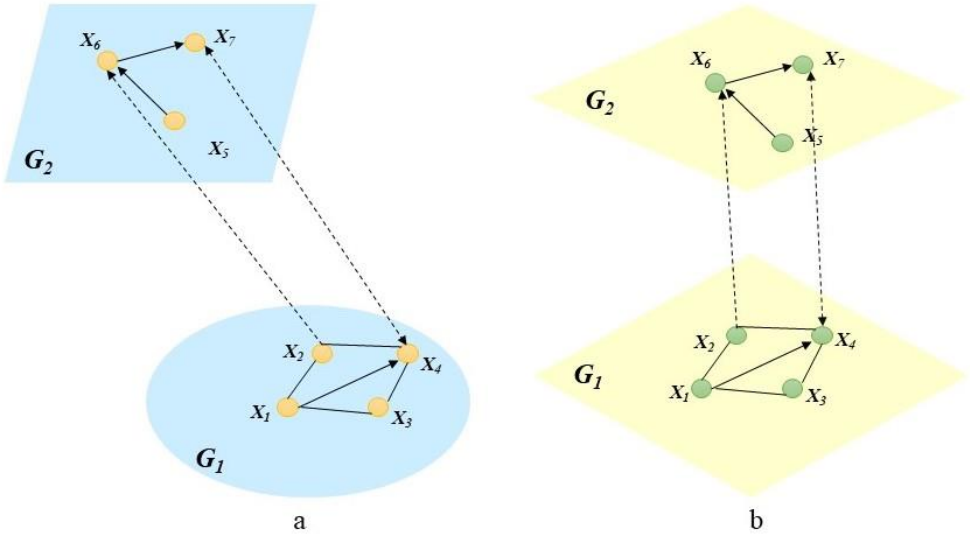



**Figure 2.** Schematic representation of the transformation of two interacting networks into a multilayer network. (**a**) networks with interactions (**b**) the structure of a multilayer network consisting of these two interacting networks. ($G_1$ and $G_2$ represent the two layers of the network respectively, the black solid line represents the interaction of the nodes within the layers, and the black dashed line represents the interaction of the nodes between the layers).

In the above section, we construct three single-layer networks for grain, disaster, and the economy based on the improved gravity model. Moreover, each layer has its own characteristics and spatial connections. Thus, to accurately describe the connection with grain, disaster, and the economy, a multilayer network model is proposed. The multiplex network is constructed by combining the above three single-layer networks, as described below [32].

The concept of co-occurrence was first proposed by the German biologist Anton de Barry, and later developed by Famintsim, Prototaxis, and others [48] to study the relationship between organisms that live in mutuality and dependence according to some material connection, resulting in a co-occurrence, synergistic evolution, or mutual inhibition. Co-occurrence, thus, refers to the interaction of organisms within themselves, and between organisms outside of them, to form a mutually beneficial relationship.

### *2.4. Characteristics of the Grain–Disaster–Economy Multilayer Network*

#### 2.4.1. Degree

In a complex multilayer network, the degree is expressed as the number of nodes associated with this node, and it measures the importance of this node in the overall complex multilayer network. The larger the node degree, the larger the number of nodes

with which this node is associated, and the more significant the node is in the multilayer network [49]. The degree of node $i$ in the multilayer network is:

$$k_i = \sum_{\alpha=1}^{m} k_i^{\alpha} = \sum_{\alpha=1}^{m} \sum_{j=1}^{n} a_{ij}^{\alpha} \tag{11}$$

where $k_i^{\alpha}$ is the degree of the node $i$ in the layer $\alpha$.

#### 2.4.2. Correlation Strength

Node correlation strength refers to the value of all connected edge weights (correlation coefficients) for that node at each layer of the network. The correlation strength of node $i$ in the multilayer network is:

$$c^{[\alpha]} = \sum_{i,j} c_{ij}^{[\alpha]} \tag{12}$$

where $c_{ij}^{[\alpha]}$ is the correlation coefficient of the connected edges between nodes $i$ and $j$ in the $\alpha$-layer association network.

#### 2.4.3. Centrality

Centrality is used to indicate the connectivity and importance of a node in a network of associations.

1. PageRank centrality

PageRank centrality (PRC) is a measure of the importance of nodes in a directed network. The higher the PageRank value, the more important the node [50].

$$R_{j\beta}^{i\alpha} = \gamma T_{j\beta}^{i\alpha} + \frac{1-r}{NL} u_{j\beta}^{i\alpha} \tag{13}$$

where $R_{j\beta}^{i\alpha}$ is the corresponding transfer tensor, $u_{j\beta}^{i\alpha}$ is a fourth-order tensor with all elements equal to 1, $N$ is the total number of nodes per layer, and $L$ is the total number of layers in a multilayer network. The stable solution of the master equation of this transfer tensor is the PRC of this multilayer network.

2. Eigenvector centrality

Eigenvector centrality ($EC$) is the sum of the weighted centrality of adjacent nodes. Nodes with higher EC scores may be connected to a large number of nodes with medium scores or to a few nodes with higher scores. The node $i$ in $\alpha$-layer network EC is defined as follows:

$$EC(i) = \lambda^{-1} \sum_{j, j \neq i} \omega_{ij}^{[\alpha]} EC(j) \tag{14}$$

where $\omega_{ij}^{[\alpha]}$ is the element of $\alpha$-layer network adjacency matrix $\Omega$, and $\lambda$ is the eigenvalue of the adjacency matrix. The EC of a node is related to both the neighbor number of neighboring nodes, as well as the EC of neighboring nodes. Equation (20) is expressed in matrix form, and $\lambda \nu = \Omega \nu$; the centrality vector $\nu$ can be derived further, that is, the eigenvector corresponding to the maximum eigenvalue of $\Omega$.

#### 2.4.4. Communities

It has been observed that many real networks exhibit a concentration of links within a special group of nodes called communities (or clusters or modules). Figure 2 shows a simple graph of the three communities. The detection of the community structure of a given network could help to discover hidden features of its topological architecture [45].

In this study, we adopt the formulation [51] to the case of weighted directed networks, as reported in the following:

$$Q = \frac{1}{2w}\sum_i\sum_j(w_{ij} - \frac{w_i w_j}{2w})\delta(C_i, C_j) \quad (15)$$

where $w_{ij}$ represents the weight of the edge between $i$ and $j$, $w_i$ and $w_j$ are the node strengths of $i$ and $j$, respectively, and $w_i = \sum_j w_{ij}$, $w_j = \sum_i w_{ij}$ are the sum of the weights of the edges attached to the country. $C_i$ is the community to which country $i$ is assigned, and $C_j$ is the community to which country $j$ is assigned. The $\delta$- function $\delta(u, v)$ is 1 if $u = v$ and 0 otherwise, and $2w = \sum_i \sum_j w_{ij}$.

$$\Delta Q = \left[\frac{\sum_{in} + k_{i,in}}{2m} - \left(\frac{\sum_{tot} + k_i}{2m}\right)^2\right] - \left[\frac{\sum_{in}}{2m} - \left(\frac{\sum_{tot}}{2m}\right)^2 - \left(\frac{k_i}{2m}\right)^2\right] \quad (16)$$

where $\sum_{in}$ is the sum of the weights of the links inside community $C$, $\sum_{tot}$ is the sum of the weights of the links incident to nodes in community $C$, $k_i$ is the sum of the weights of node $i$, $k_{i,in}$ is the sum of the weights from $i$ to nodes in community $C$, and $m$ is the sum of the weights of all the links in the network

## 3. Results and Discussion

### *3.1. Analysis of Degree*

In this study, 31 provinces in China were selected as nodes to construct a GDE multilayer network based on the gravity model and co-occurrence theory. The provinces and number of nodes in each layer of the multilayer network are the same, and the grain layer nodes are denoted as Anhui (G), the disaster layer nodes as Anhui (D), and the economy layer nodes as Anhui (E). Based on preliminary calculations, the degree value of the GDE multilayer network was obtained (Figure 3). The spatial distribution of the degree in GDE multilayer networks is shown in Figure 4. Figure 4 and Figure 6 were implemented by the MuxViz Tools package in R, and the detailed operation process of this method follows Santo Fortunato et al. [52].

In this study, we selected the top 20 provinces in the GDE multilayer network for the analysis. The results show that these node provinces are distributed in different single layers. In the grain layer, there are provinces such as Inner Mongolia, Hubei, Shandong, Anhui, and Henan. In the disaster layer, there are provinces such as Jiangxi, Hunan, Heilongjiang, Anhui, Shanxi, Henan, Shandong, and Hubei. In the economy layer, there are provinces such as Inner Mongolia, Shaanxi, Hunan, Shandong, Henan, Jiangsu, and Hubei. Moreover, the three provinces of Hubei, Shandong, and Henan simultaneously ranked in the top 20 in all three single-layer networks. Therefore, it can be concluded that these three provinces not only play a more important role in the single-layer network but also present important nodal roles in the GDE multilayer complex network; that is, there is a closer connection between grain, disaster, and the economy in all three provinces. The top 20 provinces in the grain–disaster network layer at the same time is Anhui, which means that the relationship between grain and disaster is stronger in Anhui Province, and the interaction between the grain and disaster layers is more obvious. The top 20 provinces in the disaster–economy network layer is Hunan, which means that the relationship between disaster and the economy is stronger in Hunan Province.

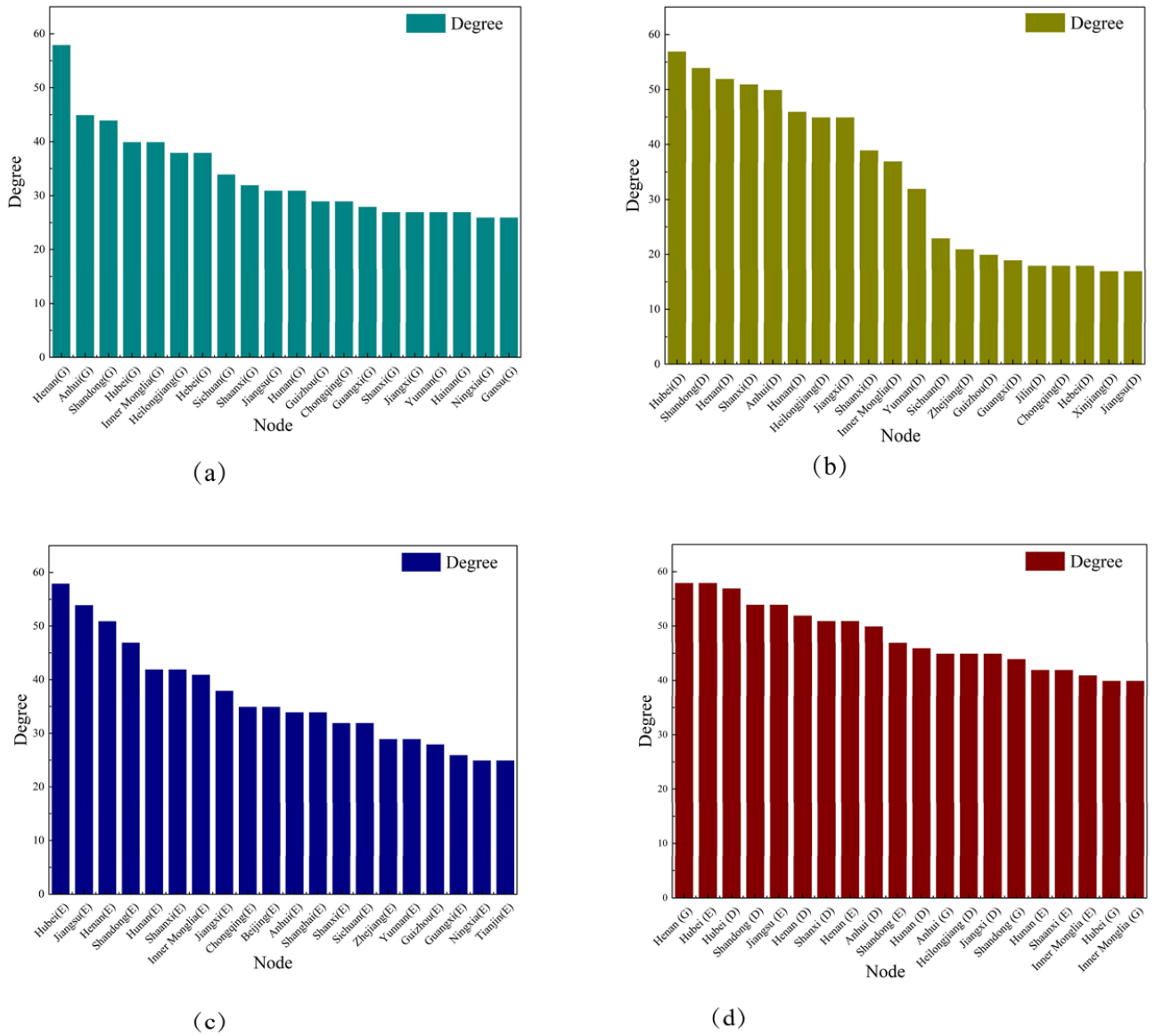



**Figure 3.** Top 20 nodes in terms of degree value in the networks. (**a**) Grain layer; (**b**) Disaster layer; (**c**) Economy layer; (**d**) The grain-disaster-economy multilayer. (The nodes with the top 20 by degree values are selected in the corresponding network above).

### *3.2. Analysis of Correlation Strength*

Based on the above analysis, the size of the node is based on the average correlation strength of node *i*, and the connection between nodes is the association between nodes in the coupled GDE multilayer network, as shown in Figure 5.

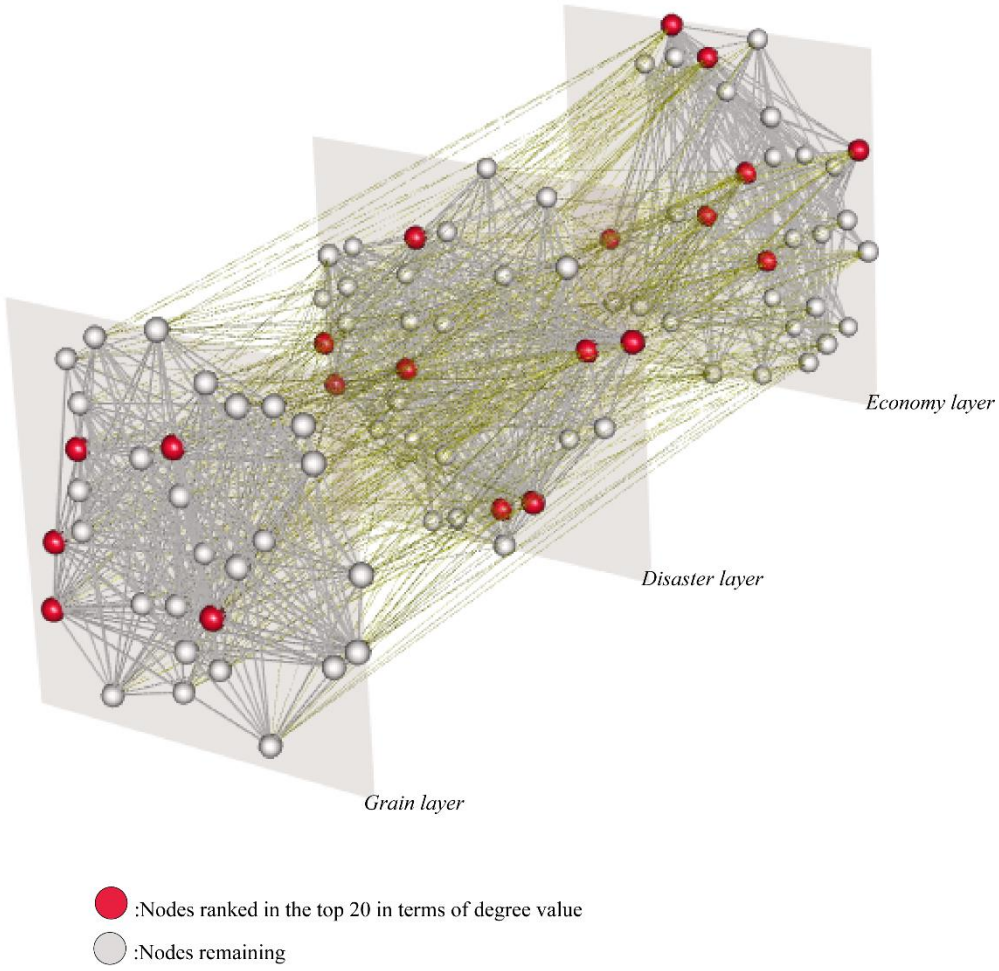



**Figure 4.** Spatial distribution of degree in grain–disaster–economy multilayer network.

In Figure 5, in the grain layer, the provinces with strong node correlation strength are mostly the main grain producing regions, such as Liaoning, Jilin, Heilongjiang, Shandong, Inner Mongolia, Jiangxi, Henan, Hubei, Jiangsu, and Anhui provinces. These nodal provinces not only have higher association strength but also have a higher number of association relationships between them and other nodes, which is consistent with the conclusion of our above analysis. In the disaster layer, provinces with strong nodal correlation are Heilongjiang, Inner Mongolia, Shandong, Henan, Anhui, Hubei, and Shanxi. These provinces are the main grain-producing areas in China, further indicating that the nodal provinces in these main grain producing areas are more prone to disaster correlations among themselves. In the economy layer, provinces with strong node correlation strength are Jiangsu, Beijing, Shanghai, Tianjin, Zhejiang, Shandong, and Fujian. Beijing and Tianjin provinces are located in the Bohai Sea Economic Zone, Jiangsu, Shanghai and Zhejiang are located in the Yangtze River Delta Economic Zone, Shandong is located in the Shandong Peninsula Blue Economic Zone, and Fujian is located in the West Coast Economic Zone, which means that these provinces are located in the more developed economic regions of China, have strong control over economic resources, and play a more important role in the formation and development of the economy layer network.

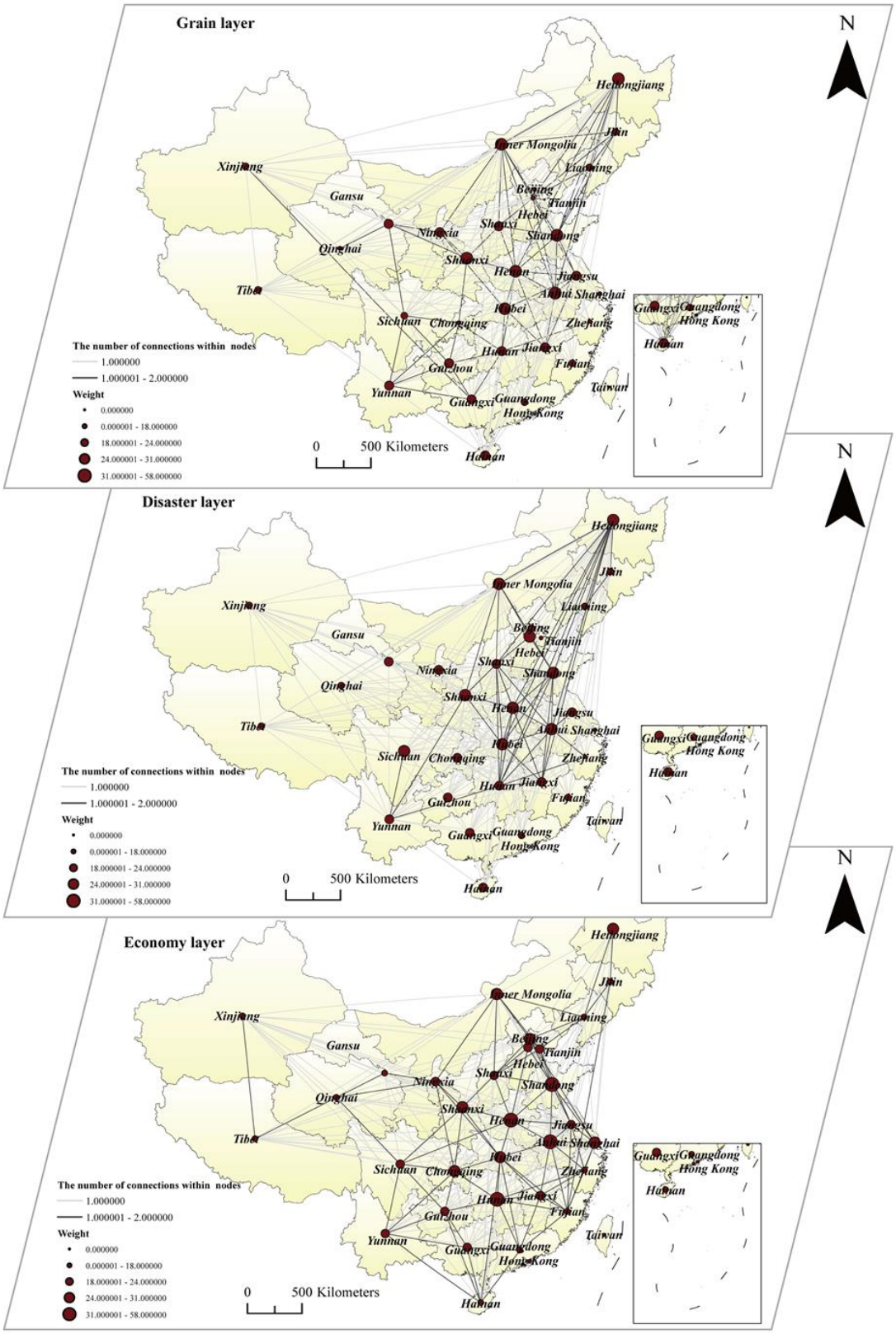



**Figure 5.** The correlation strength of node in grain–disaster–economy multilayer network in 2019.

### 3.3. Analysis of Centrality

#### 3.3.1. PageRank Centrality

The PRC of the GDE in China's provinces is shown in Figure 6a. It can be seen that in the GDE multilayer network, PRC has significant differences and obvious distribution differences in each single-layer network as well as in the multilayer network.

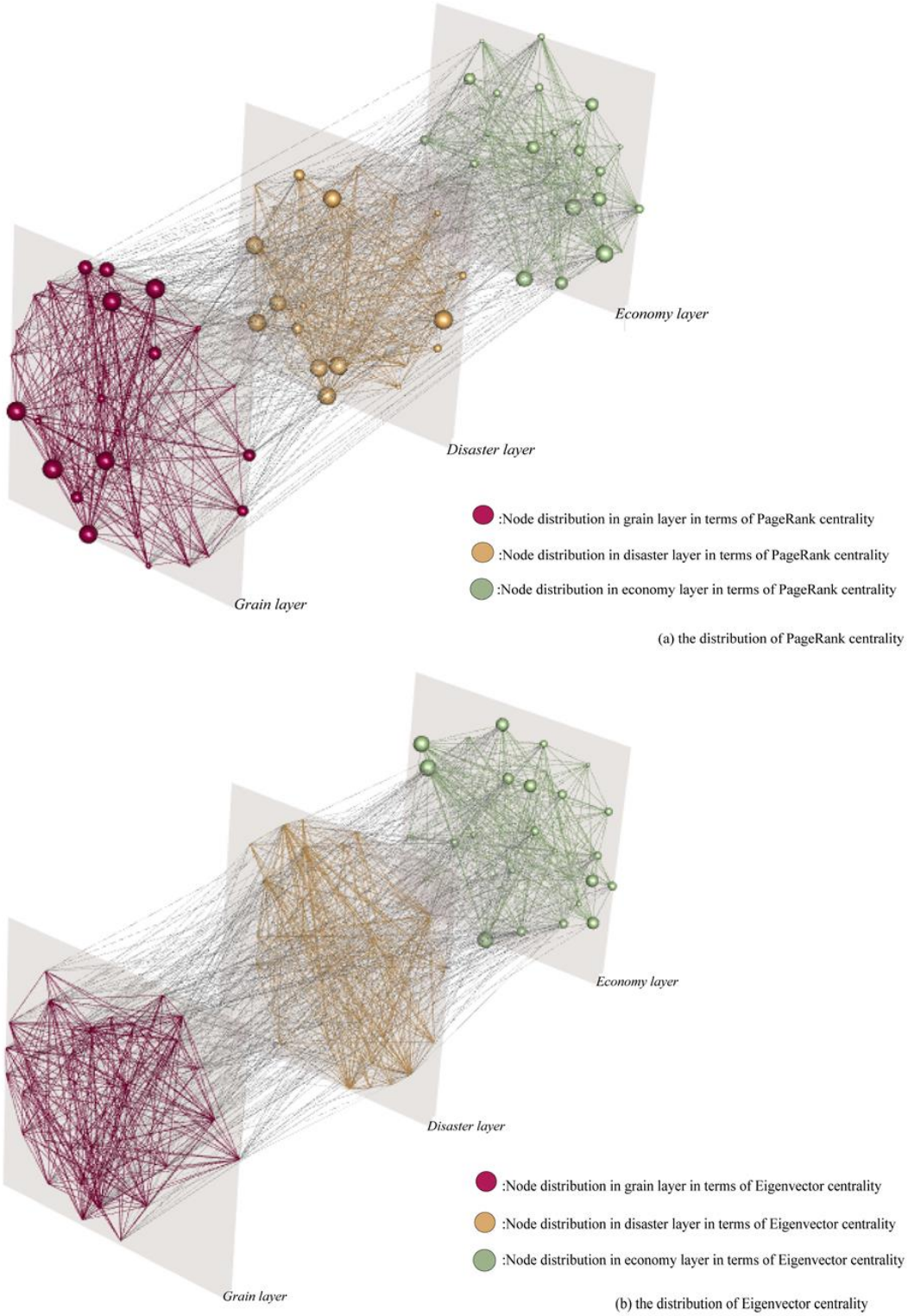



**Figure 6.** Centrality characteristics of grain–disaster–economy multilayer network.

PRC can more comprehensively reflect the characteristics of complex networks. It strengthens the association between nodes in the network and weakens the influence of connected node centrality; thus, the position of the node in the network can be measured effectively. In this study, we selected the top 20 node provinces in each layer of the network to analyze the specific position and importance of each node in the complex GDE multilayer network. The top 20 nodes in terms of PRC in the network are shown in Figure 6.

As shown above, a, b, c, and d in Figure 7 correspond to the grain, disaster, and economy single-layer networks, and the GDE multilayer network, respectively. As shown in Figure 7a, the provinces with large PageRank values in the grain single-layer network are Henan, Shandong, Inner Mongolia, Hebei, and Heilongjiang. This indicates that these provinces are the main grain-producing areas in China; thus, they assume a pivotal position in the grain single-layer network and have strong control over grain resources. The results shown in Figure 7b demonstrate that in the disaster layer network, the provinces with large PageRank values are Heilongjiang, Shanxi, Shandong, Henan, Hubei, and Jiangxi. These provinces are adjacent to each other and are susceptible to droughts and floods due to topographical factors, which are more likely to have an impact on other provinces. In Figure 7c, in the economy layer network, the provinces with large PageRank values are shown to be Jiangsu, Beijing, Shanghai, Tianjin, Zhejiang, Shandong, and Fujian. Beijing and Tianjin are located in the Bohai Sea Economic Zone, Jiangsu, Shanghai, and Zhejiang are located in the Yangtze River Delta Economic Zone, Fujian is located in the West Coast Economic Zone, which means that these provinces are located in the more developed economic regions of China; thus, these provinces are in the central hub position in the economy single-layer network and have strong control over economic resources which play a more important role in the formation and development of the economy layer network, which in turn plays an even more significant role. Figure 6d shows the top 20 nodes of the PageRank value of the GDE multilayer network, and the results show that the node provinces in the multilayer network are consistent with those in the economy single-layer network, which indicates that the economy plays a central pivotal position in the GDE multilayer network and has strong control over various resources in the multilayer network. This indicates that these nodal provinces not only occupy a central pivotal position in the economy single-layer network and have a closer connection with other provinces but also exert strong control over resources in the GDE multilayer network and play an important role in the formation and development of the multilayer network. In other words, a coupled system of coordinated development with multiple provinces as the core has been formed in China's GDE multilayer network, and these hub provinces have played an important role in the formation and development of China's GDE multilayer network by ensuring their own development while driving the development of neighboring provinces.

#### 3.3.2. Eigenvector Centrality

Figure 6b shows the EC of GDE. There are obvious differences and significant distribution differences in the EC in the GDE multilayer network. The EC shows that the importance of a node in the network depends on the importance of the node's neighboring nodes; therefore, it is a centrality measure of the influence of a node in the network. The larger the EC value of the node, the more dominant the role played by the node in the network. In this study, we selected the top 20 node provinces in each layer of the network to analyze the specific position and importance of each node in the complex GDE multilayer network. The top 20 nodes in terms of EC in the network are shown in Figure 8.

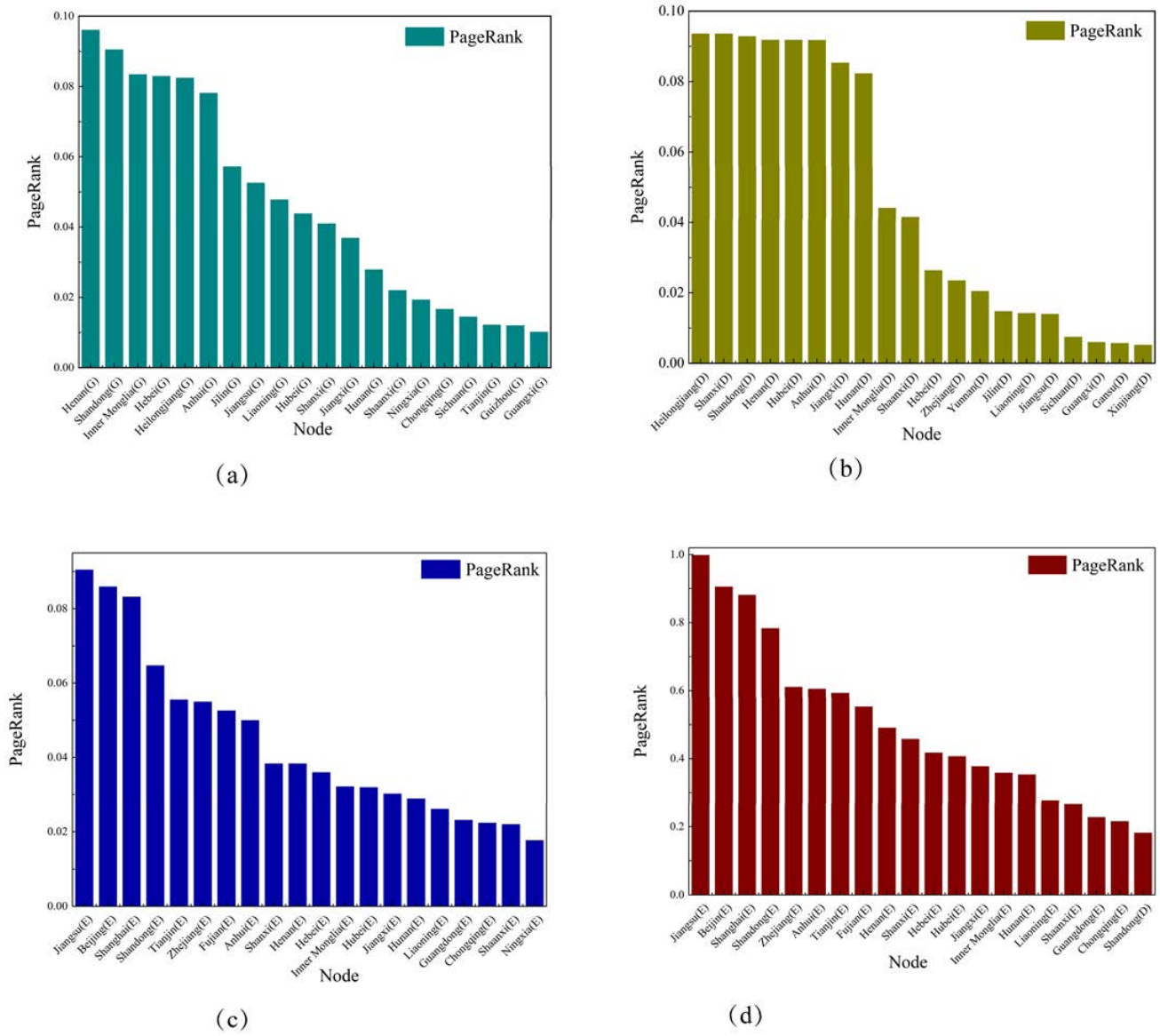



**Figure 7.** Top 20 nodes in terms of PageRank centrality in the networks. (**a**) Grain layer; (**b**) Disaster layer; (**c**) Economy layer; (**d**) The grain-disaster-economy multilayer. (The nodes with the top 20 by PageRank centrality values are selected in the corresponding network above).

In Figure 8a–d correspond to the grain, disaster, and economy single-layer networks, and the GDE multilayer network, respectively. The results show that the node provinces with the highest EC values in the grain single-layer network (Figure 8a) are Henan, Shandong, Inner Mongolia, Anhui, Heilongjiang, and Hebei. These provinces are the main grain-producing areas in China, which is consistent with the above PageRank conclusion, which indicates that these node provinces are not only in the central hub position in the grain single-layer network but the node provinces adjacent to these provinces also play an important role at the same time; the larger the EC value of the node, the greater the role of the node in the network. Henan Province is not only the main grain-producing area in China but also the largest agricultural province in China; thus, Henan Province is in the top position in both the grain and the disaster layer networks, which also indicates the close relationship between grain and disaster in Henan Province. In the disaster single-layer network, the nodal provinces with the highest EC values are Heilongjiang, Shanxi, Shandong, Henan, Hubei, Anhui, and Jiangxi, which indicates that not only are these provinces part of the disaster layer but the nodal provinces adjacent to these provinces are more susceptible

and, thus, also part of the disaster layer. Simultaneously, most of these provinces are the main grain-producing areas in China, which is consistent with the node provinces in the aforementioned grain single-layer network, indicating that there is a close correlation between disasters and grain in these node provinces. In the economy single-layer network in Figure 8c, the node provinces with the highest EC values are Jiangsu, Shanghai, Beijing, Shandong, Zhejiang, Fujian, and Tianjin, which means that these node provinces play an important role in the economy single-layer network, and the nodes adjacent to these node provinces also play an important role in the network. Provinces such as Beijing and Tianjin in the Bohai Sea economic circle, and Jiangsu, Shanghai, and Zhejiang in the Yangtze River Delta region are highly developed economies. This is consistent with the conclusion of the above PageRank value arrangement distribution of node provinces, which means that these provinces not only play an important hub role in the network but also that the node provinces that surround these provinces play an important role in regulating economic resources. The results in Figure 8d show that the nodal provinces that play an important role in the GDE multilayer network remain essentially the same as those in the economy single-layer network, which indicates that it is the economic subsystem that plays a pivotal role in the coupled GDE multilayer network system. Moreover, the EC not only indicates the important role of these nodes in the network but also that the provinces adjacent to these node provinces occupy important central pivotal positions, indicating that the coupled GDE multilayer network system in China is co-developed with the joint role of multiple core provinces.

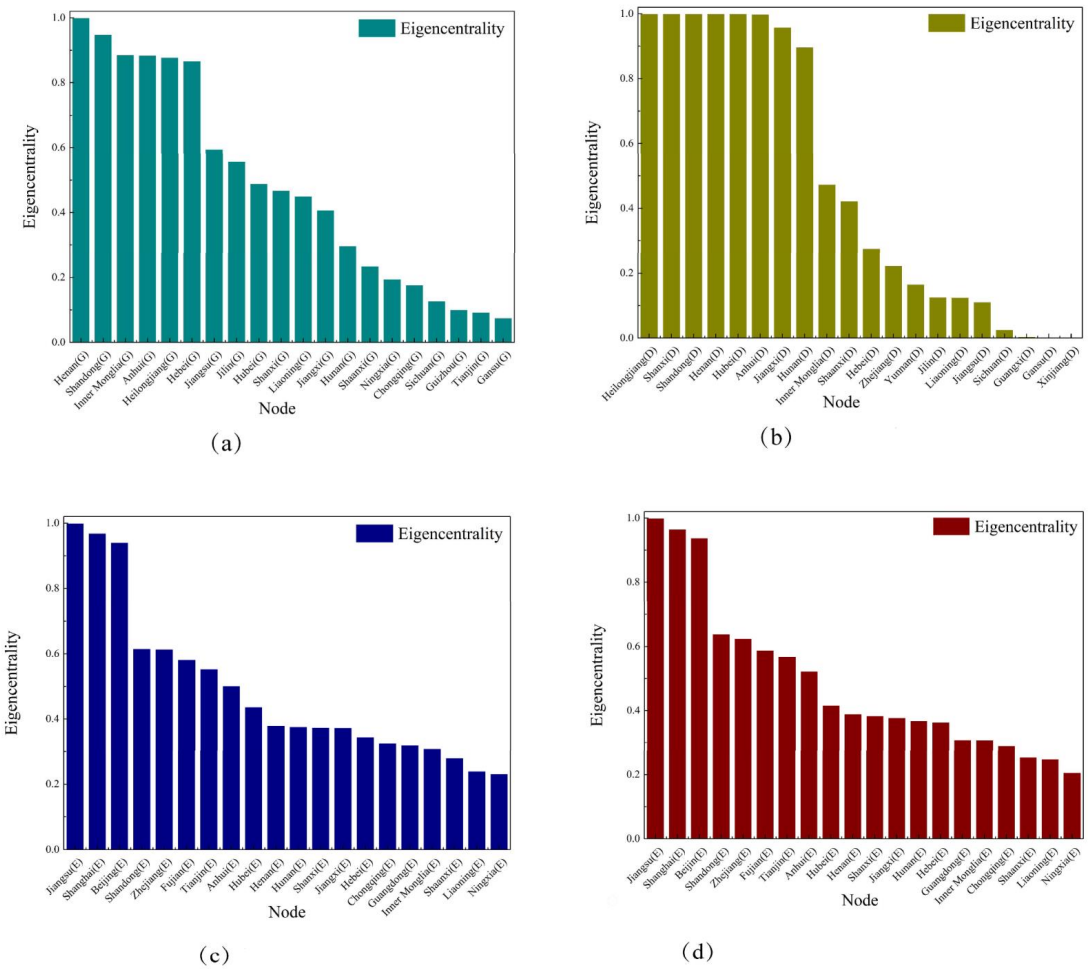
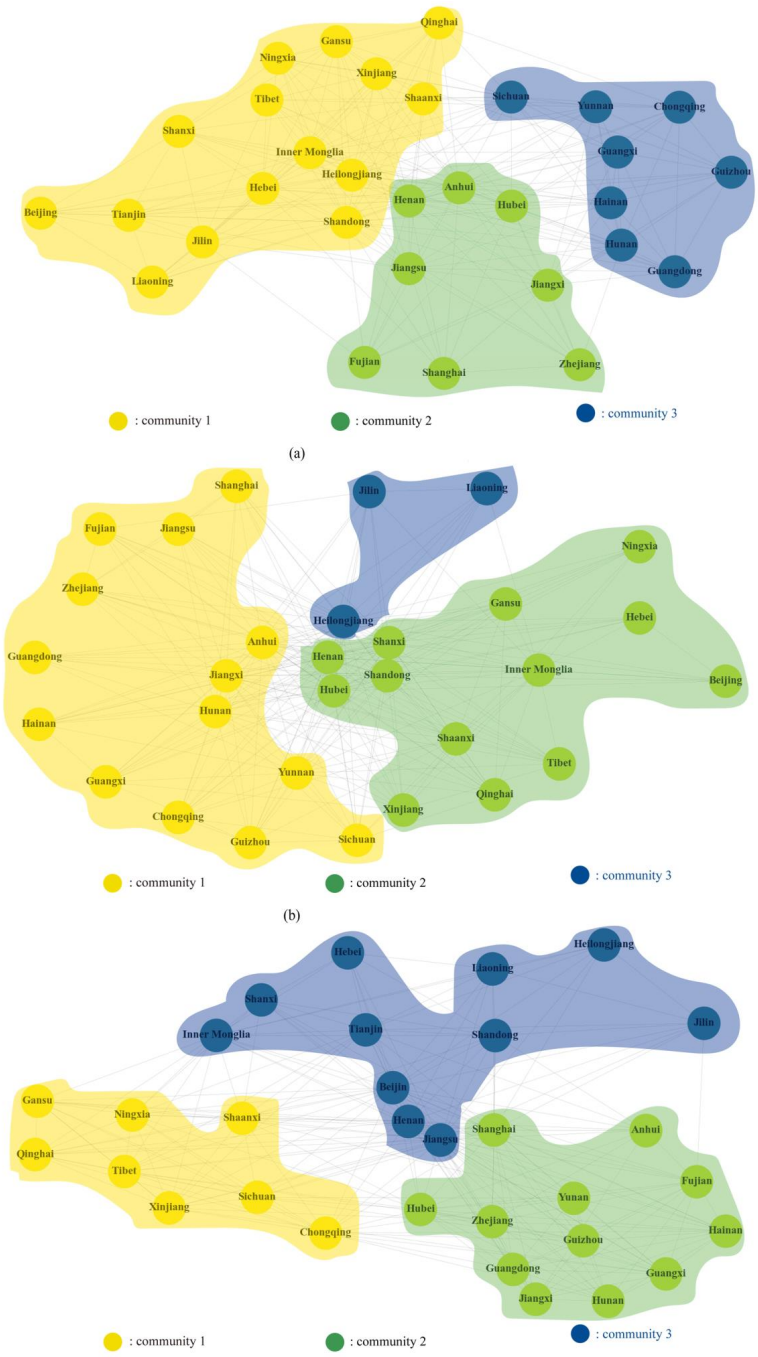



**Figure 8.** Top 20 nodes in terms of eigenvector centrality in the networks. (**a**) Grain layer; (**b**) Disaster layer; (**c**) Economy layer; (**d**) The grain-disaster-economy multilayer. (The nodes with the top 20 by Eigenvector centrality values are selected in the corresponding network above).

### *3.4. Community Detection*

Based on the Louvain algorithm, we pictured the community distribution of grain, disaster, and economy single-layer networks (Figure 9). This Figure was implemented by the Louvain Tools package in Python and the detailed operation process of this method follows Blondel et al. [51].




(**c**)

**Figure 9.** Community distribution of three single-layer networks. (**a**) Community distribution in grain layer; (**b**) Community distribution in disaster layer; (**c**) Community distribution in economy layer. (The three single-layer networks of grain, disaster, and economy are divided into three communities with different colors respectively, and the black solid line represents the association relationship between nodes in the network).

The community detection degree is 0.206, 0.08, and 0.265 for the grain, disaster, and economic monolayer networks, respectively, and is higher for the grain and economic monolayer networks and lower for the disaster monolayer network. As shown in Figure 9a, in the grain monolayer network, Community 1 includes the node provinces of Guizhou, Yunnan, Guangdong, Guangxi, Hunan, Hainan, Sichuan, and Chongqing. Community 2 has Jiangxi, Fujian, Zhejiang, Anhui, Jiangsu, Shanghai, Hubei, and Henan provinces, and Community 3 has the provinces of Heilongjiang, Shandong, Inner Mongolia, Shaanxi, Xinjiang, Jilin, Liaoning, Tianjin, and Beijing. It can be seen that most of the main grain-producing areas in China are distributed in Community 3, which means that Community 3 is in the strong position to regulate and control the grain resources; these provinces play an important role in the formation and development of China's grain monolayer network, forming a grain spatial network with the main grain-producing areas as the core development.

As shown in Figure 9b, in the disaster monolayer network, Community 1 includes the provinces of Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Chongqing, Sichuan, Guizhou, and Yunnan. Community 2 includes the provinces of Beijing, Hebei, Shanxi, Inner Mongolia, Shandong, Ningxia, and Gansu, and Community 3 includes the provinces of Liaoning, Jilin, and Heilongjiang. It can be seen that Community 1 mainly includes East China, South China, and Southwest China, Community 2 is mainly in North China and Northwest China, and Community 3 is mainly in Northeast China. The community detection module degree of China's disaster single-layer network is low, indicating that there is no obvious zonal clustering of disasters, and is mainly based on the differences in China's geographical location and topography.

As shown in Figure 9c, in the single-layer economy network, Community 1 includes Chongqing, Sichuan, Ningxia, Qinghai, Xinjiang, Gansu, and Tibet. Community 2 includes the provinces of Jiangxi, Fujian, Anhui, Guangdong, Shanghai, Zhejiang, and Hubei, and Community 3 includes the provinces of Beijing, Tianjin, Hebei, Jilin, Liaoning, Heilongjiang, and Shandong. Community 1 is mainly distributed in the western region, except for Chongqing Sichuan, which is generally economically underdeveloped, and Chongqing Sichuan belongs to the Chengdu–Chongqing Economic Zone, which has a high level of economic development and drives the economic development of the remaining western region. Community 2 is mainly distributed in the Yangtze River Delta Economic Zone, the West Coast Economic Zone, and the Pearl River Delta. The node provinces in Community 2 generally have a high level of economic development and strong ability to control and regulate economic resources, playing an important role in the formation and development of the economy single-layer network. Community 3 is mainly distributed in the Bohai Sea Economic Circle and the Blue Economic Zone of the Shandong Peninsula. Thus, the economy single-layer network has formed a network structure of multi-core development with the major economic zones in China as the core.

The community detection graph of the GDE multilayer network was obtained to further analyze the community structure of the coupled GDE multilayer system.

As shown in Figure 10, the GDE multilayer network is divided into three communities. The first community contains 16 nodes in the grain layer network, 9 nodes in the disaster layer network, and 12 nodes in the economy layer network. The second community contains 15 nodes in the grain layer network, 10 nodes in the disaster layer network, and 8 nodes in the economy layer network. The third community includes 12 nodes in the disaster layer network and 11 nodes in the economy layer network. That is, in the GDE multilayer network, the grain layer network is clustered into two communities, and both the disaster layer and the economy network are clustered into three communities.

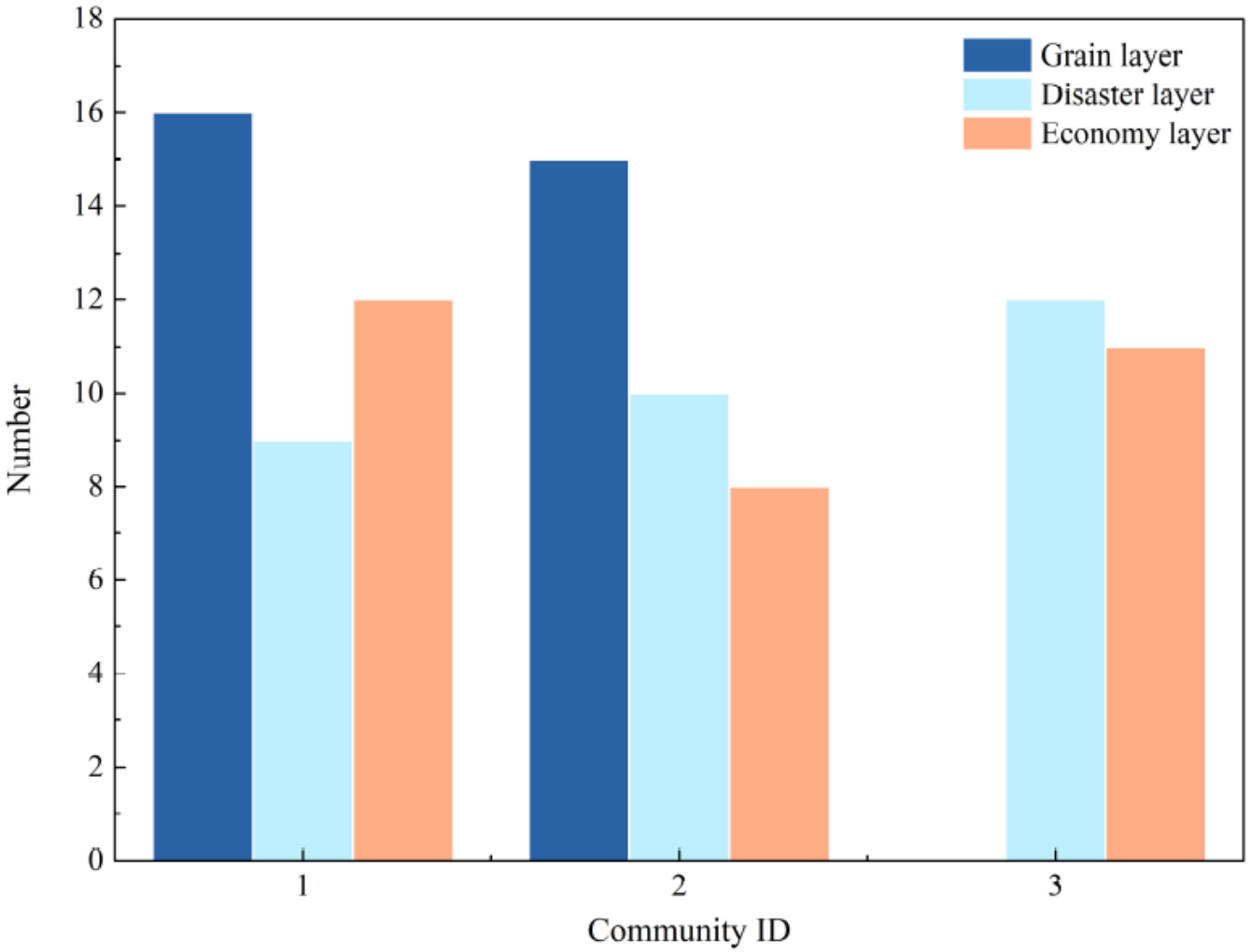



**Figure 10.** Community number of the grain–disaster–economy multilayer network.

The distribution of node clustering provinces for community detection in the GDE multilayer network was further analyzed, as shown in Figure 11. In Figure 11, the missing data in Hong Kong, Macau, and Taiwan are marked in white.

The results show that the modularity of the GDE multilayer network is 0.345, which is higher than that of the grain, disaster, and economy single-layer networks. Thus, the community clustering of the GDE multilayer network performs better. The nodes in the grain layer of Community 1 include the provinces of Henan, Jiangsu, Anhui, Hubei, Zhejiang, Jiangxi, Shanghai, Hunan, and Fujian, the nodes in the disaster layer include the provinces of Jiangsu, Hubei, Zhejiang, Jiangxi, Hunan, Fujian, Guangdong, and Shanghai, and the nodes in the economy layer include the provinces of Anhui, Hubei, Zhejiang, Jiangxi, Hunan, Yunnan, Fujian, Guangdong, and other provinces. The nodes in the grain layer in Community 2 include the provinces of Heilongjiang, Shanxi, Ningxia, Tibet, Shandong, Jilin, Liaoning, and Tianjin, the nodes in the disaster layer include the provinces of Heilongjiang, Xinjiang, Shanxi, Tibet, Shandong, Jilin, Liaoning, and Inner Mongolia, and the nodes in the economy layer include the provinces of Xinjiang, Ningxia, Tibet, Qinghai, Gansu, and Shaanxi. The nodes in the disaster layer in Community 3 are in the provinces of Ningxia, Henan, Yunnan, Guizhou, Guangxi, Hainan, and Chongqing, and the nodes in the economy layer are in the provinces of Heilongjiang, Shanxi, Shandong, Henan, Jiangsu, and Tianjin.

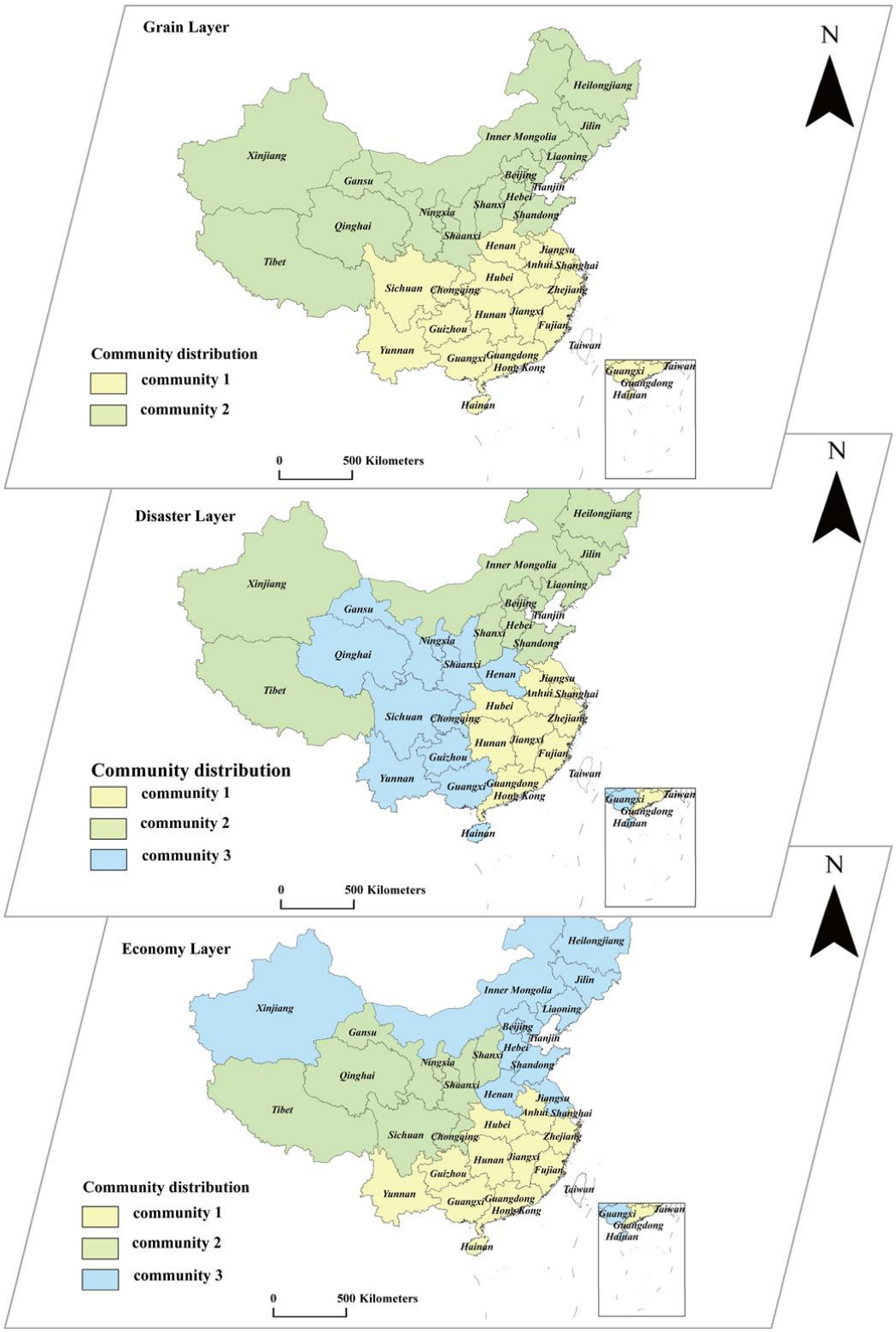



**Figure 11.** Community cluster of grain–disaster–economy multilayer network in 2019.

The provinces that assume the control and regulation of grain resources in the multilayer network of GDE are mostly in China's main grain-producing regions, which have more abundant grain resources and are never in the central hub position in the network. Provinces with a more important influence on economic resources are in the economically developed regions of China, and these provinces have a higher level of economic

development. Therefore, in summary, the GDE multilayer network in China forms a coupled multilayer network structure with the main grain-producing regions regulating and controlling grain resources, with multiple economic development areas as the core of multi-core development.

## 4. Discussion

Compared with other existing studies, the application of complex networks and co-occurrence theory to the construction of multilayer networks proposed in this paper compensates for the inability of complex networks alone to express the association of one subsystem with another in a complex system, and it clarifies the local and overall interactions among multiple systems [53].

### *4.1. Further Exploration of the Three Single-Layer Networks*

Grain, disaster, and the economy are closely related, but few studies have systematically analyzed and discussed all three. This paper shows that the nodal provinces in the main food-producing regions have a strong ability to deploy food resources, which is consistent with previous findings [10]. Further, this paper analyzes and discusses the spatial flow and association between disasters and the economy. The disaster layer does not have an obvious zoning phenomenon. Natural disasters in China are widespread and regional in nature, and the regional nature of the physical geography determines that of natural disasters [24]. Moreover, most of the provinces with greater node correlation are in the main grain-producing regions, meaning that the node provinces in the main grain-producing regions have higher correlation and these provinces are more prone to natural disasters. The spatial and temporal heterogeneity of China's grain affected by natural disasters is significant, among which drought and flood disasters have a greater impact on grain production [54]. Droughts are mainly distributed in the areas north of the Qinling and Huaihe rivers, the Huang-Huai-Hai region, and the middle and lower reaches of the Yangtze River. Floods mainly occur in the eastern regions and the plain areas with flat terrain. Therefore, provinces such as Jilin, Shanxi, Anhui, Heilongjiang, Shandong, and Hebei are more prone to natural disasters, and food production is more affected by them. Hubei, Shandong, and Henan provinces are ranked high in the node degree in the food, disaster, and economic layers, meaning that these three provinces are in the core of the three single-layer networks. Hubei, Shandong, and Henan are all in the main grain producing areas, and the implementation of some policies to promote and benefit agriculture, such as the complete abolition of the agricultural tax, minimum purchase price of grain, implementation of the "four subsidies" for agriculture, and others, as well as the continuous investment of financial support for agriculture [1], constantly improve the construction of the natural disaster prevention and control system and improve the comprehensive disaster prevention and mitigation capacity. To reduce losses due to natural disasters on food production and economic development, the economic layer has an obvious zoning phenomenon. For example, the Beijing–Tianjin–Hebei economic zone, the Yangtze River Delta, and the Pearl River Delta economic zones are the centers of economic development in China, so these nodal provinces have strong control over economic resources [55].

### *4.2. GDE Partitioning and Suggestions*

In this paper, the community detection of the coupled GDE multilayer network concludes that the community modularity of the complex system, after coupling, becomes higher, and the higher value of modularity indicates the stronger community structure delineated by the network; that is, better quality of delineation [56]. The economic subsystem plays a more critical and central role in the coupled GDE system. Therefore, based on existing grain and economic zoning, a more reasonable GDE zoning has been identified, which also provides a new perspective to realize the comprehensive and coordinated development of grain, disaster, and the economy in each region. Shanxi, Heilongjiang, and Inner Mongolia, which are the main grain-producing areas, rely on agricultural resources to

develop their economy. Thus, they should increase their investment in agricultural science and technology, promote modern agriculture, and accelerate the pace of resource transformation in accordance with national policy to reduce the plundering of resources and economic hindrance by industrial production. The nodal provinces in the Beijing–Tianjin–Hebei Economic Zone, Yangtze River Delta, and Pearl River Delta Economic Zone, such as Beijing, Tianjin, Jiangsu, Shanghai, and Zhejiang, are rich in resources with convenient transportation and are the center of China's economic development, so it is important to introduce talents to attract foreign investment and strengthen the use of resources and disaster protection at the same time. Moreover, the economic system plays a central role in the GDE coupling system; thus, these regions should further promote the development of neighboring provinces and regions while ensuring their own development. With the establishment of the national Ministry of Emergency Management, all regional governments in China should gradually improve regional emergency disaster mitigation measures so that they can respond to sudden disasters in a timely manner and reduce the impact of disasters on food production as well as economic development.

### *4.3. Limitations and Future Directions*

It should be noted that the data used in this paper are all from the statistical yearbook, and the data type is relatively singular and has limitations. In future research, multi-source data, such as remote sensing imagery data and observation data, should be used. The spatial and temporal evolution characteristics of GDE multilayer networks can be further explored in the future, and research on the characteristics of multilayer networks can be implemented by using topological data analysis and deep learning methods.

## 5. Conclusions

In order to systematically analyse the spatial characteristics and coupled relationships among the systems of grain, disaster, and the economy, a multilayer network that firstly integrates both the complex network and co-occurrence theory is constructed in this study. The multilayer network is used to clarify the local and overall interactions among multiple systems, and can reveal the coupled relationships between grain, disaster, and the economy from a new perspective. This can be used as an effective decision-making tool to identify the bottleneck and weakness in the complex systems of grain, disaster, and the economy. The corresponding proactive control measures can improve the coupled GDE multilayer network. The contributions of this study are as follows: (a) Theoretically, we establish a coupled multilayer network for grain, disaster, and the economy. This study also fills the gap in previous research, focusing on the analysis of the development of the individual systems, including grain, disaster, and the economy, or just the correlation between two of the three systems. (b) Practically, we identify the spatial coupling characteristics of the GDE multilayer network more comprehensively and scientifically, by using three aspects: degree, centrality, and community detection, which is helpful to take measures according to local conditions. This application can not only be extended to measure the interconnectedness of grain, disaster, and the economy in other national or international governments systems but also provides a reference for similar complex coupling systems.

Some meaningful conclusions are drawn:

(1) The assessment of node degree, PRC, and EC values enables to identify the most critical nodes. The node in the main grain-producing areas have stronger control over grain resources and have an important position in the grain single-layer network, which is consistent with previous findings [10]. These provinces also have higher node correlations in the disaster single-layer network, indicating that they are more prone to disasters. Provinces in the Beijing–Tianjin–Hebei Economic Zone, Yangtze River Delta, and Pearl River Delta Economic Zone are the core regions of China's economic development and have a high level of ability to coordinate economic resources.

(2) The analysis of the topological structure of the coupled GDE multilayer network, shows that the economic subsystem is in a more central and pivotal position, playing an

important role in the formation and development of the multilayer network compared with the grain and disaster subsystems. This means that provinces with greater control over economic resources are better able to achieve the coordinated co-development of grain, disaster readiness, and the economy in the region. Therefore, the economic development of each region should be promoted in a targeted manner so that the coupled GDE multilayer network can develop together more sustainably.

(3) The modularity of the coupled GDE multilayer network is 0.345, which is higher than that of its three single-layer networks. It further indicates that the community division of the GDE system in China is more reasonable and advantageous compared with the existing single food and economic divisions in China. This is also helpful in taking various measures according to local conditions to improve the common sustainable development of grain, disaster, and the economy in different regions of China.

**Author Contributions:** Conceptualization, Zongyi He, Junli Li and Hongjiao Qu; methodology, Junli Li and Hongjiao Qu; formal analysis, Wenwen Xin, Weiyin Wang and Cheng Zhou; writing—original draft preparation, Junli Li and Hongjiao Qu; writing—review and editing, Junli Li and Hongjiao Qu; visualization, Junli Li and Hongjiao Qu; project adminintration, Junli Li; funding acquisition, Junli Li. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was financially supported by the Natural Science Foundation of Anhui Province (Grant No. 2108085MD29) and in part by the National Natural Science Foundation of China (Grant No. 41571400).

**Data Availability Statement:** The data used to support the findings of this study area are available from the corresponding author upon request via email.

**Conflicts of Interest:** The authors declare that they have no conflicts of interest.

## References

1. Xie, K.; Ding, M.J.; Xin, L.J.; Chen, L.W. Spatial-temporal Patterns of Grain Output and Its Spatial Relationship with Economic Development at the County Level in China. *Econ. Geogr.* **2021**, *41*, 167–175.
2. Wu, Z.D.; Zhang, Y.; Wu, Z.L.; Cao, X.C.; Liang, X.Y.; Wu, L.Z. Study on the spatio-temperoal evolution and influencing factors of economic efficiency of generalized water use for crop production in China's major grain-producing area. *Resour. Environ. Yangtze Basin* **2021**, *30*, 2763–2777.
3. Schneider, P.; Asch, F. Rice production and food security in Asian Mega deltas—A review on characteristics, vulnerabilities and agricultural adaptation options to cope with climate change. *J. Agron. Crop Sci.* **2020**, *206*, 491–503. [CrossRef]
4. Liu, M.J.; Wang, B.; Zhong, J.T. Population-Economic-Grain Regional Difference and Spatial Pattern of Qinghai Province in the Past 30 Years. *Northwest Popul. J.* **2021**, *42*, 113–124.
5. Piao, S.; Ciais, P.; Huang, Y.; Shen, Z.; Peng, S.; Li, J.; Zhou, L.; Liu, H.; Ma, Y.; Ding, Y.; et al. The impacts of climate change on water resources and agriculture in China. *Nature* **2010**, *467*, 43–51. [CrossRef]
6. Li, J.; Wu, W.; Ye, X.; Jiang, H.; Gan, R.; Wu, H.; He, J.; Jiang, Y. Innovative trend analysis of main agriculture natural hazards in China during 1989–2014. *Nat. Hazards* **2018**, *95*, 677–720. [CrossRef]
7. Zhang, J. Risk Assessment of Drought Disaster in the Maize-Growing Region of Songliao Plain, China. *Agric. Ecosyst. Environ.* **2004**, *102*, 133–153. [CrossRef]
8. Zhou, L.; Wu, X.; Xu, Z.; Fujita, H. Emergency decision making for natural disasters: An overview. *Int. J. Disaster Risk Reduct.* **2018**, *27*, 567–576. [CrossRef]
9. Chen, S.; Chen, B. Tracking Inter-Regional Carbon Flows: A Hybrid Network Model. *Environ. Sci. Technol.* **2016**, *50*, 4731–4741. [CrossRef]
10. Feng, Y.; Hou, M.Y.; Yao, S.B. Structural characteristics and formation mechanism of spatial correlation network of grain production in China. *Acta Geogr. Sin.* **2020**, *75*, 2380–2395.
11. Chen, M.; Shang, S.; Li, W. Integrated Modeling Approach for Sustainable Land-Water-Food Nexus Management. *Agriculture* **2020**, *10*, 104. [CrossRef]
12. Hanna, R.L. Drivers and challenges for transnational land–water–food investments by the Middle East and North Africa region. *Wiley Interdiscip. Rev. Water* **2020**, *7*, e1415. [CrossRef]
13. Khan, A.; Chenggang, Y.; Khan, G.; Muhammad, F. The dilemma of natural disasters: Impact on economy, fiscal position, and foreign direct investment alongside Belt and Road Initiative countries. *Sci. Total Environ.* **2020**, *743*, 140578. [CrossRef]
14. Naqvi, A.; Monasterolo, I. Assessing the cascading impacts of natural disasters in a multi-layer behavioral network framework. *Sci. Rep.* **2021**, *11*, 20146. [CrossRef]

15. Belasen, A.R.; Dai, C. When oceans attack: Assessing the impact of hurricanes on localized taxable sales. *Ann. Reg. Sci.* **2014**, *52*, 325–342. [CrossRef]
16. Mu, J.E.; Chen, Y. Impacts of large natural disasters on regional income. *Nat. Hazards* **2016**, *83*, 1485–1503. [CrossRef]
17. Pu, C.; Liu, Z.; Pan, X.; Addai, B. The impact of natural disasters on China's macroeconomy. *Environ. Sci. Pollut. Res.* **2020**, *27*, 43987–43998. [CrossRef]
18. Weerasekara, S.; Wilson, C.; Lee, B.; Hoang, V.-N.; Managi, S.; Rajapaksa, D. The impacts of climate induced disasters on the economy: Winners and losers in Sri Lanka. *Ecol. Econ.* **2021**, *185*, 107043. [CrossRef]
19. Du, X.; Jin, X.; Yang, X.; Yang, X.; Xiang, X.; Zhou, Y. Spatial-temporal pattern changes of main agriculture natural disasters in China during 1990–2011. *J. Geogr. Sci.* **2015**, *25*, 387–398. [CrossRef]
20. Chen, H.; Liang, Z.; Liu, Y.; Jiang, Q.; Xie, S. Effects of Drought and Flood on Crop Production in China Across 1949–2015: Apatial Heterogeneity Analysis with Bayesian Hierarchical Modeling. *Nat. Hazards* **2018**, *92*, 525–541. [CrossRef]
21. Xie, Z.; Xu, J.; Deng, Y. Risk analysis and evaluation of agricultural drought disaster in the major grain-producing areas, China. *Geomat. Nat. Hazards Risk* **2015**, *7*, 1091387. [CrossRef]
22. Wu, Y.; Que, W.; Liu, Y.-G.; Cao, L.; Liu, S.-B.; Zhang, J. Is resilience capacity index of Chinese region performing well? Evidence from 26 provinces. *Ecol. Indic.* **2020**, *112*, 106088. [CrossRef]
23. Choi, C. Does economic growth really reduce disaster damages? Index decomposition analysis for the relationship between disaster damages, urbanization and economic growth and its implications. *Int. J. Urban Sci.* **2016**, *20*, 188–205. [CrossRef]
24. Wang, Q.; Zhang, Q.-P.; Liu, Y.-Y.; Tong, L.-J.; Zhang, Y.-Z.; Li, X.-Y.; Li, J.-L. Characterizing the spatial distribution of typical natural disaster vulnerability in China from 2010 to 2017. *Nat. Hazards* **2019**, *100*, 3–15. [CrossRef]
25. Rashid, S.; Dorosh, P.; Alemu, D. Grain markets, disaster management, and public stocks: Lessons from Ethiopia. *Glob. Food Secur.* **2018**, *19*, 31–39. [CrossRef]
26. Jiang, L.; Wu, S.; Liu, Y.; Yang, C. Grain security assessment in Bangladesh based on supply-demand balance analysis. *PLoS ONE* **2021**, *16*, e0252187. [CrossRef] [PubMed]
27. Lv, F.; Deng, L.; Zhang, Z.; Wang, Z.; Wu, Q.; Qiao, J. Multiscale analysis of factors affecting food security in China, 1980–2017. *Environ. Sci. Pollut. Res.* **2021**, 1–15. [CrossRef] [PubMed]
28. Hu, G.; Xu, X.; Gao, J.; Guo, X.C. Node Importance Recognition Algorithm Based on Adjacency Information Entropy in Networks. Systems Engineering. *Theor. Pract.* **2020**, *40*, 714–725.
29. Ning, L.; Zhou, Y.; Cheng, C.; Ye, S.; Shen, S. Using a Complex Network to Analyze the Effects of the Three Gorges Dam on Water Level Fluctuation in Poyang Lake. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 470. [CrossRef]
30. Shen, S.; Huang, J.; Cheng, C.; Zhang, T.; Murzintcev, N.; Gao, P. Spatiotemporal Evolution of the Online Social Network after a Natural Disaster. *ISPRS Int. J. Geo-Inf.* **2021**, *10*, 744. [CrossRef]
31. Scala, A.; D'Aostino, G. *Networks of Networks: The Last Frontier of Complexity*; Springer Publishing Company: Berlin/Heidelberg, Germany, 2014.
32. Wei, C.; Shuai, Q.; Manrui, J.; Cheng, J. The Construction of Multilayer Stock Network Model. *Physics A* **2021**, *565*. [CrossRef]
33. Huang, Q.-A.; Zhao, J.-C.; Wu, X.-Q. Financial risk propagation between Chinese and American stock markets based on multilayer networks. *Phys. A Stat. Mech. Appl.* **2021**, *586*, 126445. [CrossRef]
34. Xie, F.; Ma, M.; Ren, C. Research on multilayer network structure characteristics from a higher-order model: The case of a Chinese high-speed railway system. *Phys. A Stat. Mech. Appl.* **2021**, *586*, 126473. [CrossRef]
35. Ren, B.; Li, H.; Shi, J.; Liu, Y.; Qi, Y. Identifying the key sectors and paths of the embodied energy in BRICS nations: A weighted multilayer network approach. *Energy* **2021**, *239*, 122091. [CrossRef]
36. Federico, B.; Giulia, C.; Iacopini, I.; Latora, V.; Lucas, M.; Patania, A.; Young, J.-G.; Petri, G. Networks beyond pairwise interactions: Structure and dynamics. *Phys. Rep.* **2020**, *874*, 1–92.
37. Shi, D.; Chen, G.; Thong, W.W.K.; Yan, X.-Y. Searching for Optimal Network Topology with Best Possible Synchronizability. *IEEE Circuits Syst. Mag.* **2013**, *13*, 66–75. [CrossRef]
38. Wang, R.; Song, S.; Lu, N.; Zhu, Y. Application of Co-Occurrence Analysis in Text Knowledge Mining. *J. Libr. Sci. China* **2007**, *2*, 59–64. [CrossRef]
39. Alrahhal, H.; Alrahhal, M.S.; Jamous, R.; Jambi, K. A Symbiotic Relationship Based Leader Approach for Privacy Protection in Location Based Services. *ISPRS Int. J. Geo-Inf.* **2020**, *9*, 408. [CrossRef]
40. Dai, L.; Wang, L.; Liang, T.; Zhang, Y.; Li, J.; Xiao, J.; Dong, L.; Zhang, H. Geostatistical Analyses and Co-Occurrence Correlations of Heavy Metals Distribution with Various Types of Land Use Within a Watershed in Eastern QingHai-Tibet Plateau, China. *Sci. Total Environ.* **2019**, *653*, 849–859. [CrossRef]
41. Ma, B.; Wang, H.; Dsouza, M.; Lou, J.; He, Y.; Dai, Z.; Brookes, P.C.; Xu, J.; Gilbert, J.A. Geographic patterns of co-occurrence network topological features for soil microbiota at continental scale in eastern China. *ISME J.* **2016**, *10*, 1891–1901. [CrossRef]
42. Shi, H.; García-Reyes, M.; Jacox, M.G.; Rykaczewski, R.R.; Black, B.A.; Bograd, S.J.; Sydeman, W.J. Co-occurrence of California Drought and Northeast Pacific Marine Heatwaves Under Climate Change. *Geophys. Res. Lett.* **2021**, *48*, e2021GL092765. [CrossRef]
43. Yang, Y.; Shi, Y.; Kerfahi, D.; Ogwu, M.C.; Wang, J.; Dong, K.; Takahashi, K.; Moroenyane, I.; Adams, J.M. Elevation-related climate trends dominate fungal co-occurrence network structure and the abundance of keystone taxa on Mt. Norikura, Japan. *Sci. Total Environ.* **2021**, *799*, 149368. [CrossRef]

44. Guo, J.; Mao, K.; Zhao, Y.; Lu, Z.; Xiaoping, L. Impact of Climate on Food Security in Mainland China: A New Perspective Based on Characteristics of Major Agricultural Natural Disasters and Grain Loss. *Sustainability* **2019**, *11*, 869. [CrossRef]
45. Boccaletti, S.; Bianconi, G.; Criado, R.; del Genio, C.; Gomez-Gardenes, J.; Romance, M.; Sendiña-Nadal, I.; Wang, Z.; Zanin, M. The structure and dynamics of multilayer networks. *Phys. Rep.* **2014**, *544*, 1–122. [CrossRef]
46. Stewart, J.Q. Demographic Gravitation: Evidence and Applications. *Sociometry* **1948**, *11*, 31. [CrossRef]
47. Donges, J.F.; Schultz, H.C.H.; Marwan, N.; Zou, Y.; Kurths, J. Investigating the topology of interacting networks. *Eur. Phys. J. B* **2011**, *84*, 635–651. [CrossRef]
48. Li, H.; Wang, H.; Yang, Y.; Zhao, R. Regional Coordination and Security of Water–Energy–Food Symbiosis in Northeastern China. *Sustainability* **2021**, *13*, 1326. [CrossRef]
49. Battiston, F.; Nicosia, V.; Latora, V. Structural measures for multiplex networks. *Phys. Rev. E* **2014**, *89*, 032804. [CrossRef] [PubMed]
50. Solé-Ribalta, A.; De Domenico, M.; Gómez, S.; Arenas, A. Random walk centrality in interconnected multilayer networks. *Phys. D Nonlinear Phenom.* **2016**, *323*, 73–79. [CrossRef]
51. Blondel, V.D.; Guillaume, J.-L.; Lambiotte, R.; Lefebvre, E. Fast unfolding of communities in large networks. *J. Stat. Mech. Theory Exp.* **2008**, *2008*, P10008. [CrossRef]
52. Fortunato, S.; Hric, D. Community detection in networks: A user guide. *Phys. Rep.* **2016**, *659*, 1–44. [CrossRef]
53. He, L.; Mao, J.; Hu, C.; Xiao, Z. Carbon emission regulation and operations in the supply chain supernetwork under stringent carbon policy. *J. Clean. Prod.* **2019**, *238*, 117652. [CrossRef]
54. Zhao, Y.H.; Guo, J.P.; Mao, K.B.; Xiang, Y.N.; Li, Y.H.; Han, J.Q.; Wu, N. Spatio-temporal distribution of typical natural disasters and grain disaster lossesin China from 1949 to 2015. *Acta Geogr. Sin.* **2017**, *72*, 1261–1276.
55. Liu, G.F.; Ju, W.J.; Ye, J.M.; Chu, G.M. Analysis and Prediction of the Coupled and Coordinated Development of Resource Utilization-Ecological Environment-Economic Growth: A Case Study of Provinces along the Silk Road Economic Belt. *Ecolo. Econ.* **2021**, *37*, 191–200.
56. Guimerà, R.; Sales-Pardo, M.; Amaral, L.A.N. Modularity from fluctuations in random graphs and complex networks. *Phys. Rev. E* **2004**, *70*, 025101. [CrossRef]