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Economic and virtual water multilayer networks in China☆

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A R T I C L E I N F O

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A B S T R A C T

Supply chains are complex systems that can be conceptualized as networks. Several studies have examined the structural properties of economic networks (i.e., given in units of financial value) and virtual water supply chain networks (i.e., where economic connections are reported in terms of their embodied water). In both cases, connections both within and between economic sectors are important to fully represent structural network properties, highlighting the importance of multilayer network analyses. The similarities and differences between economic and virtual water multilayer networks are yet to be well understood. The goal of this study is to consistently compare the economic and virtual water multilayer networks within China. Environmentally extended multi-regional input–output (EE-MRIO) data is used to build multilayer networks between 31 provinces and 41 economic sectors (nodes are province-sectors) for commodities and services in the year 2017, using both economic [¥] and virtual water [m^3] weights. This study shows that virtual water multilayer networks are relevant to address questions of water sustainability, scarcity, and hazards in supply chains, but that examining virtual water networks in isolation may not identify the economically important core nodes. Consideration of both economic and embedded resource networks could enhance our understanding of complex supply chains.

1. Introduction

Supply chains are interconnected multisectoral systems, composed of connections both between and within economic sectors. For this reason, supply chains can be conceptualized as complex multilayer networks (Bellamy and Basole, 2013). Multilayer networks explicitly include the connections between layers in a network, in addition to the connections within a single monolayer network. Multilayer networks have been increasingly used to represent economic supply chains, in order to more accurately capture their structural features (Boccaletti et al., 2014; Kivelä et al., 2014). Multilayer approaches are also increasingly being used to understand embodied resource flows in supply chains, including virtual water flows (Garcia et al., 2021). This makes it important to understand how economic and embedded resource multilayer networks compare and contrast with one another. The goal of this study is to consistently compare the multilayer features of economic and virtual water supply chains within China.

Recent studies have demonstrated that multilayer networks capture characteristics of node- and system-level dynamics that differ to monolayer versions of the graphs (Buldyrev et al., 2010; Nicosia et al., 2017). For example, differences were found between the topological connectivity of the multilayer and monolayer network of global trade (Alves et al., 2018). Additionally, research has shown that analyzing only

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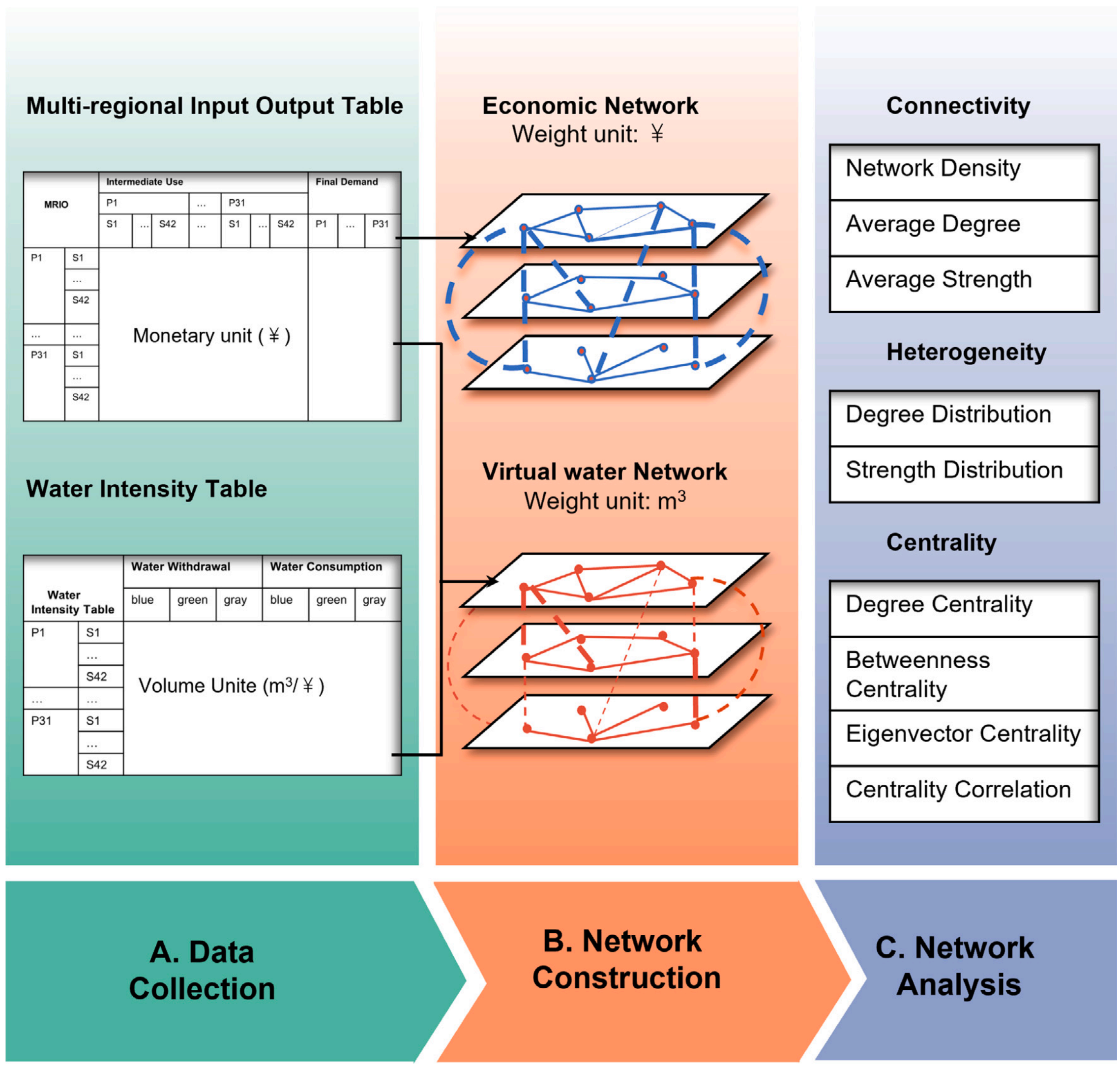

Fig. 1. Overview of the study methodology. There are three main stages: A. Data collection: Multi-Regional Input–Output (MRIO) data quantifies inter and intra sectoral connections in economic units [¥]. Water intensity data quantifies the water use in economic production. B. Network Construction: Water intensity data is combined with MRIO data to obtain virtual water multilayer networks. In the economic and virtual water multilayer networks nodes are province-sectors and links connect nodes both within and across economic layers. C. Network Analysis: Complex network statistics are used to determine the properties of the economic and virtual water multilayer networks.

the monolayer structure of a network may lead to the erroneous identification of central nodes (De Domenico et al., 2015), which is often one of the main goals of complex network analyses. For this reason, multilayer networks are increasingly being used to characterize complex networks, including economic (Barigozzi et al., 2010; Caschili et al., 2016; Alves et al., 2019; Gomez et al., 2020) and virtual water networks (Garcia et al., 2021). Virtual water networks capture the water embedded in supply chains from production to consumption. In this way, virtual water networks quantify teleconnections in societal uses of water across space. Monolayer virtual water networks have identified the structural features of global trade (Konar et al., 2011) and domestic supply chains (Dang et al., 2015; Chini et al., 2017, 2018; Dalin et al., 2014). Virtual water networks have been shown to exhibit nontrivial connectivity patterns (Konar et al., 2011; Dalin et al., 2012; Fang and Chen, 2015), which is the hallmark of any complex network (Newman, 2003). Yet, multilayer virtual water networks exhibit quantitatively and qualitatively different results than their monolayer counterparts. Multilayer virtual water networks can overcome truncation errors and information loss associated with monolayer representations (Garcia et al., 2021). For this reason, the literature has increasingly been highlighting the importance of using a multilayer approach to analyze virtual water networks. However, to our knowledge, there has not yet been an evaluation of how multilayer virtual water networks compare with the multilayer economic networks from which they are built.

China is a suitable case study for this research because it is a key nation for global trade, which relies on its domestic production and supply chains (Qu et al., 2018). Economic production in China often occurs in water-stressed locations, such as the relatively arid north, which has extensive agricultural production (Zhao et al., 2020). Importantly, the Chinese government produces national statistical information on its provincial production and supply chain connections through Multi-Regional Input–Output (MRIO) accounts. MRIO data characterize the connections both within economic sectors (in different spatial locations) and across economic sectors. MRIO data thus provides the essential information to build a multilayer network. To incorporate embodied resources, MRIO data is combined with a resource consumption vector, to yield an Environmentally Extended MRIO database (EE-MRIO) (Wiedmann et al., 2007; Wiedmann and Barrett, 2013; Yang et al., 2013). Both MRIO and EE-MRIO data capture spatial and sectoral interdependencies within an economy. In this study, we focus on China's virtual water multilayer by combining economic MRIO data with statistics on water use.

The goal of this paper is to understand how economic and virtual water multilayer networks compare with one another. The EE-MRIO

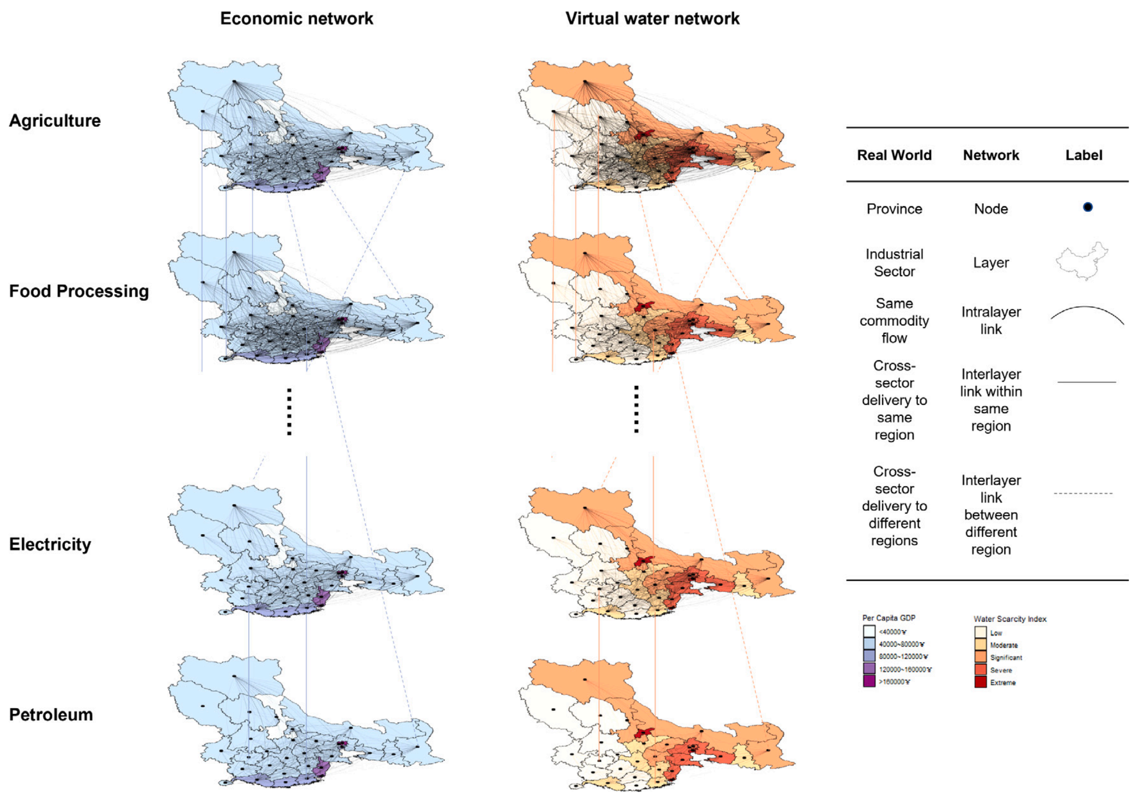

Fig. 2. Illustration of the economic and virtual water multilayer networks. A subsample of the 41 economic sectors are shown. Each layer shows the 31 provinces within China. A node in the multilayer network is a province-sector. Intralayer links provide connections within an economic sector while interlayer links provide inter-sectoral connections. The weights of the links are [¥] in the economic network and water volume [m^3] in the virtual water network.

framework with water use data is used to transform the economic network into virtual water weights. The native units of the China MRIO database are financial value (e.g., ¥), referred to as the "economic network". Combining the economic network with the water used in production transforms the database into a "virtual water network" in units of water volume (i.e., m^3). The economic and virtual water supply chain multilayer networks within China trace commodity and service flows between 31 provinces and 41 economic sectors for the year 2017 (the most recent year of available data). The following research questions are addressed in this project: (1) What is the relationship between the economic and virtual water multilayer networks? (2) What are the similarities and differences between the economic and virtual water multilayer networks? (3) What are the key locations and economic sectors in the economic and virtual water multilayer network in China? Addressing these questions will help future researchers understand the systematic relationship between economic and virtual water multilayer networks.

2. Methods

This section details the methodologies in this study. Fig. 1 provides an overview of the methodological approach, in which there are three main stages. First, the necessary information on water resources use and multi-regional input–output tables are collected. Second, the economic and water use information is structured as a network. Third, complex network statistics are used to evaluate the structural characteristics of the economic and virtual water flow networks within China.

2.1. Data collection

This study rely on two main table: the MRIO table and water intensity table. Firstly, an MRIO table was developed for the year 2017, following the same method used to develop the 2012 MRIO (Zhang et al., 2012), which has been applied to study a variety of environmental issues in China (Zhang et al., 2019). We excluded the water production and supply sector to avoid double counting. Next, we construct the water intensity table based on several sources. Blue water consumption intensities for the agricultural sectors were collected from the provincial Water Resource Bulletin (PWRB, Provincial Water Resources Bureau, 2017). The provincial Water Resource Bulletin also provides the overall industry water consumption (including the service sector) for each province. The water intensity data was collected from Zhang and Anadon (2013) to derive the percentage of provincial blue water consumption for all industry-sectors belonging to each sector and then allocate the industrial water consumption by sectors. The energy sectors (including electricity, natural gas, coal and petroleum) are converted from per physical unit water content from Zhang and Anadon (2013) to per monetary unit according to the energy production in year 2007. Specifically, the per monetary unit water per province and per energy sector is derived by dividing the corresponding total monetary value of the production achieved from the MRIO table by total production water consumption, where total production water consumption equals per physical unit water content times total production (i.e., money unit water intensity = $\frac{\text{physical unit water intensity} \times \text{total production}}{\text{total money value of the production}}$). Under the assumption that the percentages for each province remain constant, the year 2007 data with provincial industrial water consumption from Water Resource Bulletin and total output data in monetary units from MRIO tables were used to get sector-wise blue water intensities. All blue water consumption intensities by economic sector is shown in the Supporting Information.

2.2. Network construction

The economic network (M) in monetary units [¥] was built using the 2017 MRIO table to calculate the value movement across provinces and economic sectors in China (see Section 2.2.1). The virtual water

(VW) network is created by combining the M network with the water intensity matrix (see Section 2.2.2). The fluxes in the VW network are reported in water volumes [m^3]. Fig. 2 illustrates the multilayer networks of China considered in this study. Each node in the multilayer network is a province-sector and intra-layer links represent spatial connections within an economic sector and inter-layer links are connections across economic sectors. The multiplex network formulation thus captures both spatial and economic sector dependencies within China.

2.2.1. Inter-provincial economic flows

MRIO methods are used to estimate the spatially-explicit domestic value chain of China. The standard MRIO model can be represented according to Eq. (1):

$$\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1} \cdot \mathbf{Y} = \mathbf{L} \cdot \mathbf{Y} \tag{1}$$

where **X** is the total output matrix [¥] combining the intermediate use and final consumption in each regional sector. **A** defines the technical coefficient matrix, which is derived from the intermediate matrix to show the relationship of one sector using the output of other sectors as input materials. **Y** represents the final demand matrix [¥], which records the consumption of output from different areas and sectors for different regions. $\mathbf{L} = (\mathbf{I} - \mathbf{A})^{-1}$ is the 'Leontief inverse matrix' or the 'total requirements matrix', where **I** is an identity matrix (Leontief, 1967). A detailed derivation of the MRIO formula is provided in the Supporting Information (SI).

The standard MRIO equation can be converted to Eq. (2) to depict the economic flow, which is the cornerstone of multilayer network construction:

$$\mathbf{W} = \mathbf{L} \cdot \hat{\mathbf{Y}} \tag{2}$$

where, $\hat{\mathbf{Y}}$ is a square diagonal matrix with the elements of total final demand vector on the main diagonal. For the economic network in China, each of the 41 economic sectors in the MRIO dataset represents a single layer. Each layer includes the same 31 nodes representing the 31 provinces. The weights of the directed edges are financial value flow determined by the matrix $\mathbf{W} = \{w_{R_iR_j}^{S_mS_n}\}$. $w_{R_iR_j}^{S_mS_n}$ represents the flow of sector m commodity in region i to sector n in region j.

2.2.2. Inter-provincial virtual water flows

The multilayer setting is the same for the VW multilayer network. Accordingly, the VW network multilayer has the same layer and nodes but different weights (i.e., virtual water volume rather than financial value). The EE-MRIO method was used to estimate VW flows among provinces in China at the sector level. An EE-MRIO model links the environmental impacts or resource use to the flow of goods and services in an economy through an environmental extension matrix, also known as an environmental satellite account. Resource use in this study is consumptive water use for economic production. The EE-MRIO approach enables us to account for blue water use throughout the entire production chain of China, as given by Eq. (3):

$$\mathbf{Q} = \hat{\mathbf{E}} \cdot (\mathbf{I} - \mathbf{A})^{-1} \cdot \hat{\mathbf{Y}} = \hat{\mathbf{E}} \cdot \mathbf{L} \cdot \hat{\mathbf{Y}} \tag{3}$$

where **Q** denotes the blue water consumption embedded in final demand. E denotes the environmental extension vectors, which are composed of blue water intensities per unit of sectoral output for different sectors by province. $\hat{\mathbf{E}}$ is the diagonalized vector of water intensity. In this way, the **Q** driven by $\hat{\mathbf{Y}}$ was calculated with the established Leontief inverse matrix, **L**. The weights of the VW multilayer were thus determined by the matrix **Q**.

2.3. Multilayer analysis

The structure of these multilayer networks is characterized by their connectivity, heterogeneity, and centrality. Multiplex metrics were calculated by functions from the NetworkX library (Version 2.5.1) in Python 3.7 (Hagberg et al., 2008). The economic (M) and virtual water (VW) networks are directed and weighted multilayer networks. The nodes in the diagram represent 31 different provinces. Each layer represents a different economic sector. There are intralayer (solid lines) and interlayer (dashed lines) edges as shown in Fig. 1. The intralayer links represent flows between regions (nodes) in the same economic sector (layer), and the interlayer links refer to flows between regions (nodes) across different sectors (layers), following the multilayer network terminology.

2.3.1. Connectivity

The connectivity of the network can be characterized by the network density, average degree, and average strength:

Network density is the number of existing links divided by the potential number of links and is calculated by $p = M/[N(N-1)]$, where N is the number of nodes in the network, M is the number of links and $N(N-1)$ is the number of potential links. Due to the existence of self-loop (i.e., edge that connects a vertex to itself), the value of network density can be larger than 1.

Average degree of the network is the average number of connections of each nodes over the whole network.

Average strength of the network is the average weight of connected links of each node over the whole network.

2.3.2. Heterogeneity

To shed light on the different attributes of different types of nodes and edges, the heterogeneity of the network is described with:

Degree (k) of the node is the number of edges incident on it. For a directed matrix, there are two types of degree: in-degree (k_{in}) and out-degree (k_{out}). k_{in} is the summation of incoming links for each node ($k_{R_iS_m}^{in} = \sum_R \sum_S e_{R_jS_n \to R_iS_m}$). k_{out} is the summation of outgoing links for each node $k_{R_iS_m}^{out} = \sum_R \sum_S e_{R_iS_m \to R_jS_n}$. The total degree is $k_{R_iS_m}^{total} = k_{R_iS_m}^{in} + k_{R_iS_m}^{out}$. $e_{R_jS_n \to R_iS_m}$ equals 1 when there is a link from node R_jS_n to R_iS_m, otherwise equals to 0.

Strength (S) refers to the weight of link, which in this case are the trade amount and VW amount. The node strength is determined by summing all weights of links connected to each node: in-strength ($s_{R_iS_m}^{in} = \sum_R \sum_S w_{R_jS_n \to R_iS_m}$), out-strength ($s_{R_iS_m}^{out} = \sum_R \sum_S w_{R_iS_m \to R_jS_n}$), and total strength ($s_{R_iS_m}^{total} = s_{R_iS_m}^{in} + s_{R_iS_m}^{out}$).

Strength distribution of multilayer is defined as the distribution depict the probability that a node chosen randomly has strength S. The strength distribution can be further classified into probability distribution of the in-strength and out-strength of each node over the intralayers and interlayers in the multilayers.

2.3.3. Centrality

Centrality indices (C) quantify the importance of nodes within a network. Three of the most commonly used centrality indices are applied here: degree centrality, betweenness centrality, and eigenvector centrality (Freeman, 1978; Bonacich, 1987; Costa et al., 2007).

Degree centrality (C_d) refers the number of edges incident on a node in a network as shown in 2.3.1.

Betweenness centrality (C_b) is a index to measure the influence of nodes on the spread of flow in a graph. It is often used to find nodes that act as bridges connecting one part of the graph to another. We employed the random walk betweenness centrality algorithm developed by Newman (2005) instead of the shortest path betweenness centrality method because the networks in this study are dense and only considering shortest paths loses information. Additionally, the random walk approach more closely represent the real world ability to meander between locations. In real-world supply chains, goods might not be moved solely via the shortest, most direct routes in the network.

Eigenvector centrality (C_e) is a relative score. For each node, connections to high-scoring nodes contribute more to scores than

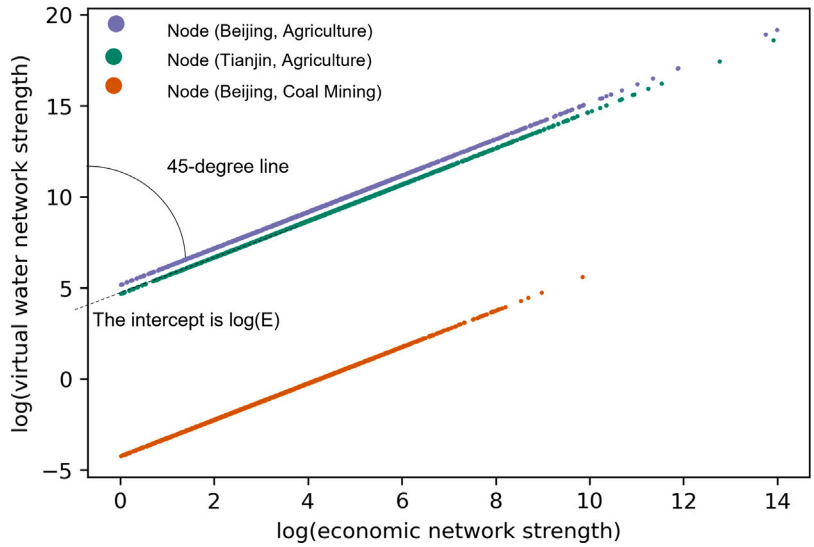

Fig. 3. Relationship between the network weights of the virtual water and economic multilayer network of China. The natural log of network strength is plotted. Data points represent the weight of the in-strength link from the target node.

Table 1
Summary statistics of the topological properties of the intralayer and interlayer multilayer of China.

Density		
Total	Intralayer	Interlayer
75%	79%	75%
Degree		
Total node	Average degree total	Average degree in/out
1271	1150	957

connections to low-scoring nodes. A high eigenvector score means that the node is connected to many nodes that have high scores themselves. "left" eigenvector centrality, which corresponds to the in-degrees in the graph was computed using the original directed networks. Reversing the graph leads to the out-edges eigenvector centrality, which is known as the "right" eigenvector (Bonacich, 1987; Newman, 2010).

3. Results and discussions

3.1. What is the relationship between the economic and virtual water multilayer networks?

The topological characteristics are the same across economic and virtual water multilayer networks, since no weights are involved when only connectivity is considered. Both the economic and virtual water multilayer networks have high density. The high connectivity of the VW network is inherited from the underlying M multilayer. These dense networks are formed by the close association of regions and industries. The average degree in/out of China's multilayer network is 957 (of 1271 total nodes; see Table 1), meaning that each node receives/supplies commodities with about three-fourths of the other nodes in the network. This highlights that the topological structure of the economic and virtual networks are identical, since the virtual water multilayer network is built from the underlying economic multilayer.

The economic and virtual water multilayer networks are both relatively dense, with a density of ~75% (listed in Table 1). Interestingly, this means that the virtual water multilayer of China is denser than the virtual water multilayer of the United States (~65%), which was presented by Garcia et al. (2021). China may have a more dense network than the United States due to the fact that information on connections between nodes are available at a more coarse spatial resolution. However, the density within and between layers of the network in China is similar, which is the same pattern that was found to exist in the virtual water multilayer network in the United States (Garcia et al., 2021). The density of the intralayer is slightly higher than the interlayer density for the multilayers in China (refer to Table 1).

Incorporating link intensities differentiates the economic from the virtual water multilayer network. The strength of the multilayer sheds light on the intensity of connections in the networks when the weights are taken into account. The average strength of the M and VW networks is 1.52×10^8 ¥ and 1.91×10^5 m^3, respectively. To illustrate the relationship between the strength of the M and VW networks, the dependence of W and VW as shown in Fig. 3 were investigated using the weights of two multilayers. There are two main observations of the log–log strength plot. First, for different nodes, the slope of the strength line will be a 45 degree line. The intercept is the logarithm of the water intensity. These relationships are not surprising as they can be derived mathematically from Eq. (3).

These results highlight that the connectivity structure of economic networks and embedded resource networks that are built from that primary network are identical. Economic and virtual water networks diverge when their weights are explicitly considered. The formulation of the EE-MRIO methodology leads to the relationship between virtual water and economic weights that is shown in Fig. 3.

3.2. What are the similarities and differences between the economic and virtual water multilayer networks?

The M and VW in-strength and out-strength distributions are shown in Fig. 4. The distributions of the strength for both networks are heavy-tailed with no clear definite functional form. The right-skewed distribution shows a high level of heterogeneity in the supply chain system. A two-sample Kolmogorov–Smirnov test (ks test) was used to test whether the two probability distributions are different. The in-strength of the interlayer and intralayer for the VW network are from different distributions. This means that the VW interlayer and intralayer may arise from different behavior patterns. High peak in-strength interlayer arises from the existence of a dominant absorbing sector, that requires a considerable amount of upstream supply chain water. The flat in-strength intralayer distribution shows that there are more frequent but small volumes of inter-regional trading of goods within the same sector.

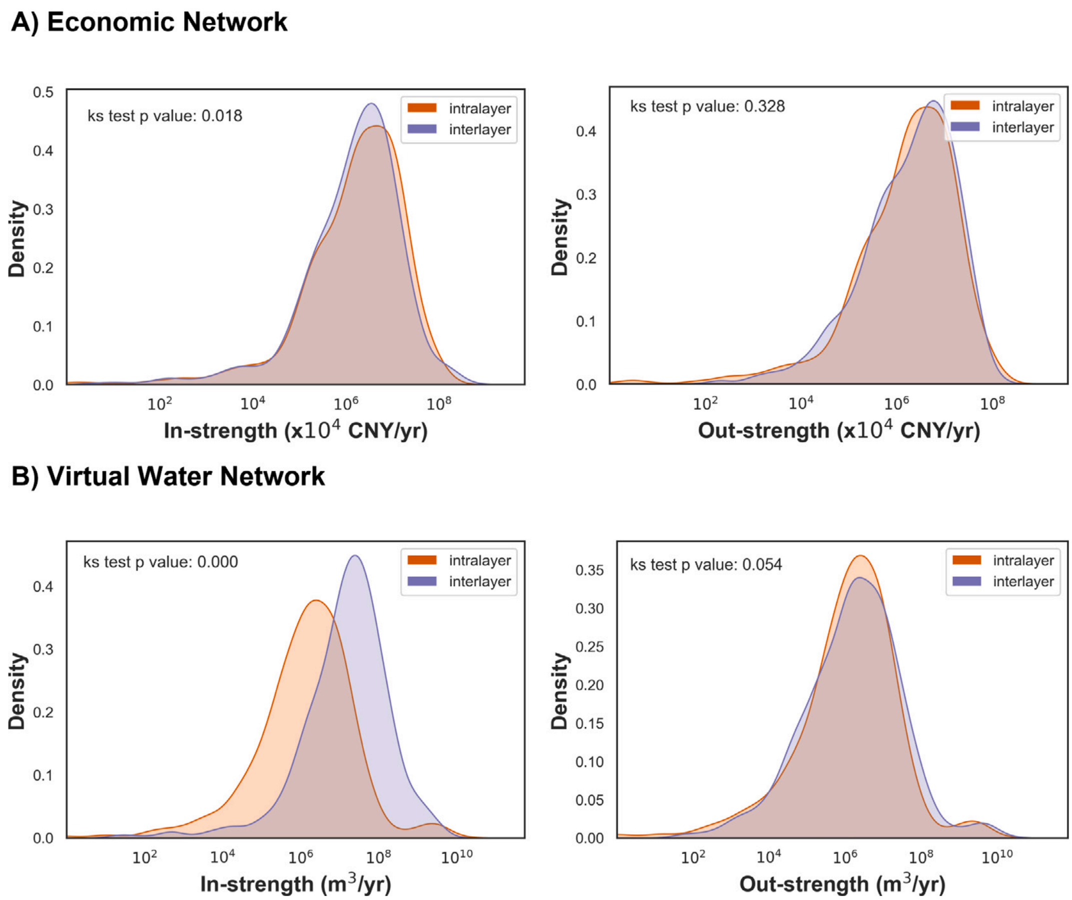

Fig. 4. Probability density function (pdf) of node in-strength (left) and out-strength (right) for the (A) economic and (B) virtual water multilayer network. The pdfs of in-strength and out-strength are shown by intralayer and interlayer. A two-sample Kolmogorov–Smirnov test (ks test) was used to test whether the two probability distributions are different, with the null hypothesis that the two datasets come from the same distribution, the alternative hypothesis that they come from different distributions and 0.01 as the selected significance level.

The same disparity between interlayer and intralayer distributions is not present in the VW out-strength and M network. This means that monetary resources are more uniformly distributed to downstream economic sectors in a national economy. This is distinct to the way in which virtual water volumetric inflows contribute to downstream sectors. The probability distribution of virtual water interlayer flows has a higher mean, which shows that virtual water flows to downstream sectors in a lumpy way and does not remain in primary economic sectors, such as agriculture. This differences in transmission of monetary flows versus virtual water volumes across economic sectors represents an important difference between the economic and virtual water multilayers in China.

Garcia et al. (2021) also concluded that interlayer flows are greater than intralayer flows for the in-strength in the VW network of the United States. The disparity of the intra- and inter-layer are not related to the amount of commodity and industry trade (in money unit) because there is no apparent difference between the intra- and interlayer in-strength for the M network. This implies that the in-strength distinctions in intralayer and interlayer behavior arise from the water consumption intensity matrix. In particular, agriculture is the primary sector that causes the large flow from the water-intense primary sector into the downstream sectors instead of flowing within the same sector. The probability distribution function of VW in-strength highlights that it is particularly important to perform multilayer analyses on virtual water systems. This is because monolayer networks will likely miss the connections in supply chains that redistribute water across intermediate sectors before reaching final consumers.

Further, the strength distribution for selected sectors (layers) was examined as in Fig. 5. The shape and characteristics of the in-strength and out-strength probability density functions vary from layer to layer, which is further justification for the multilayer analysis rather than monolayer analysis. All the layers follows unimodal distribution with one clear peak, which corroborates this same observation in the US virtual water multilayer (Garcia et al., 2021). The property of peak distribution is inherited from the M network. Peaked strength distributions are a typical feature of spatial networks like commodity and service supply chain, when factors such as geographic location, transit costs, and distance are important (Barthélemy, 2011).

3.3. What are the key locations and economic sectors in the economic and virtual water multilayer network in China?

Centrality is the tool to evaluate which nodes are the most "important" to the network. Fig. 6 shows the betweenness centrality for some selected layers. A detailed table for all nodes and centrality types is provided in the SI. The important nodes for the M and VW network are quite different. The agriculture layer stands out as having a high betweenness centrality in the virtual water multiplex, but not in the economic multiplex. In particular, the high water intensity of the agriculture sector in Xinjiang makes Xinjiang stand out as an important node of the VW network. The importance of some provinces which are economically developed with very high economic output, like Jiangsu, Sichuan, Hubei, are shown to have high centrality in the M network but do not register as having high centrality in the VW network. These findings illustrate that centrality metrics pick up on important differences between economic and virtual water multilayer networks.

High spatial heterogeneity in the agricultural water use intensity contributes to differences in the regional centrality between the VW

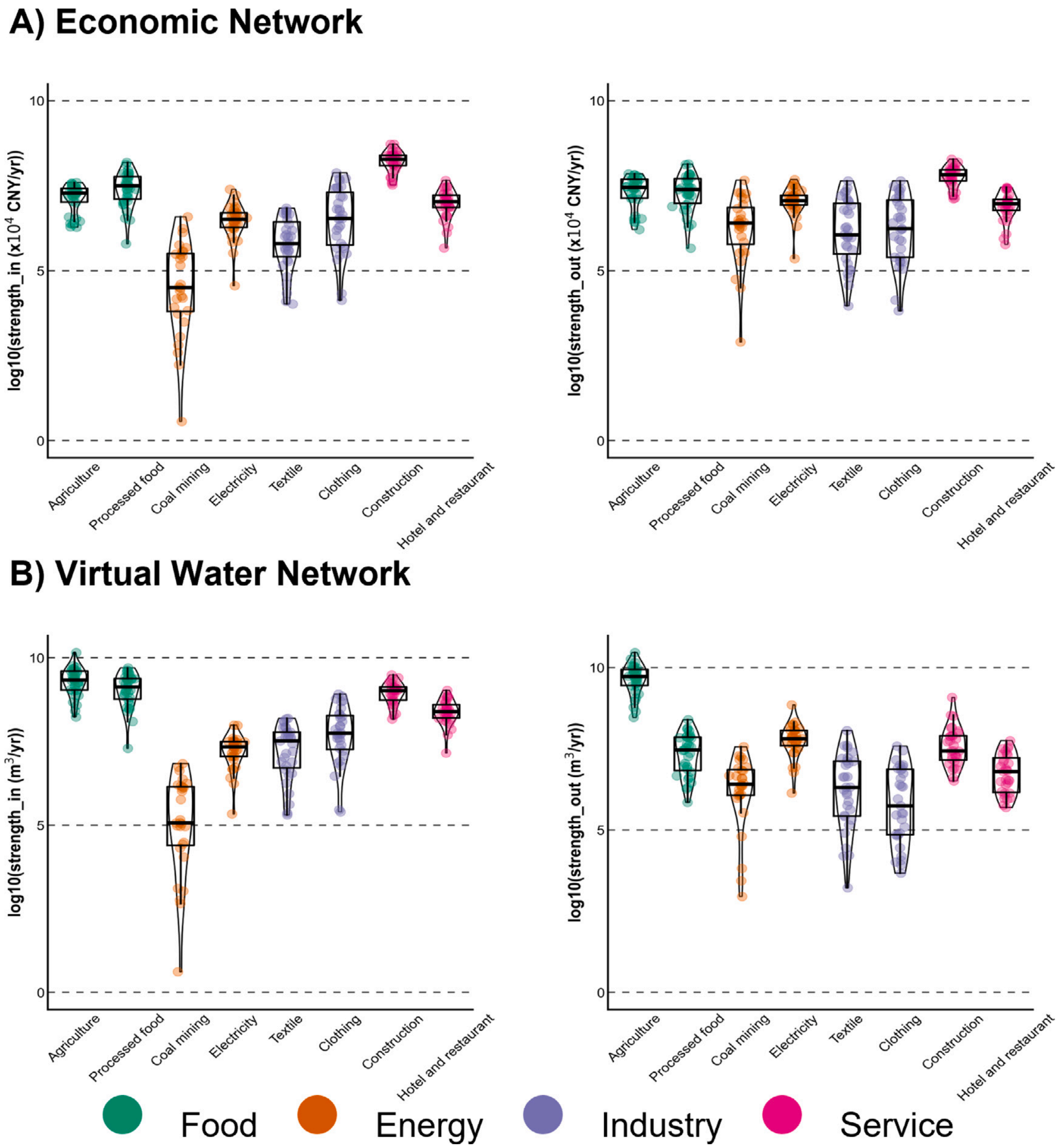

Fig. 5. Probability density function (pdf) of node in-strength (left) and out-strength (right) for selected layers in the (A) economic and (B) virtual water multilayer network. Information is provided for different macrosectors.

and M networks. There is a high correlation between the regional centrality and agriculture centrality in the VW network. Interestingly, the heterogeneity in water use in the primary economic sector like agriculture is not transmitted to the downstream economic sector, like food processing in terms of centrality, even though we saw in Fig. 5 that water inflows are important to downstream sectors in the economy. The betweenness centrality for M network shows more heterogeneity for different layers and the regional centrality.

Fig. 7 shows the correlation between several centrality indices for M and VW network. The correlation between the strength centrality and degree centrality is relatively higher in network M than VW network. The general weak correlation explains why the weighted network analysis is important especially for the VW network. Compared to betweenness centrality, eigenvector centrality is less related to the strength centrality for both network. On one hand, the high correlation relationship between strength centrality and betweenness centrality implies that the nodes with high strength are also more active to encourage trade between different nodes. On the other hand, the result of eigenvector centrality differs significantly from that of other strength-based centrality indices, which implies that eigenvector centrality can evaluate the importance of nodes from a different prospective.

Other than the correlation between centrality indices within each network, we are also interested in whether the same node has similar topology and centrality across different networks. Firstly, it is not surprising that the correlation of total degree centrality for M network and VW network is equal to 1, and so is the degree in and degree out centrality for two multilayers, that is because these two networks have the same topological structure. However, the correlation between the two networks is weaker in terms of strength. There is almost no relationship between the betweenness centrality and eigenvector centrality between the two networks. In other words, the network centrality changes dramatically under different weight schemes. This means that it is important to consider the appropriate weighting scheme to use in order to determine the central locations or sectors in a multiplex network. In particular, these findings may highlight that virtual water networks emphasize issues of embedded water, but may miss some important economic aspects of supply chains.

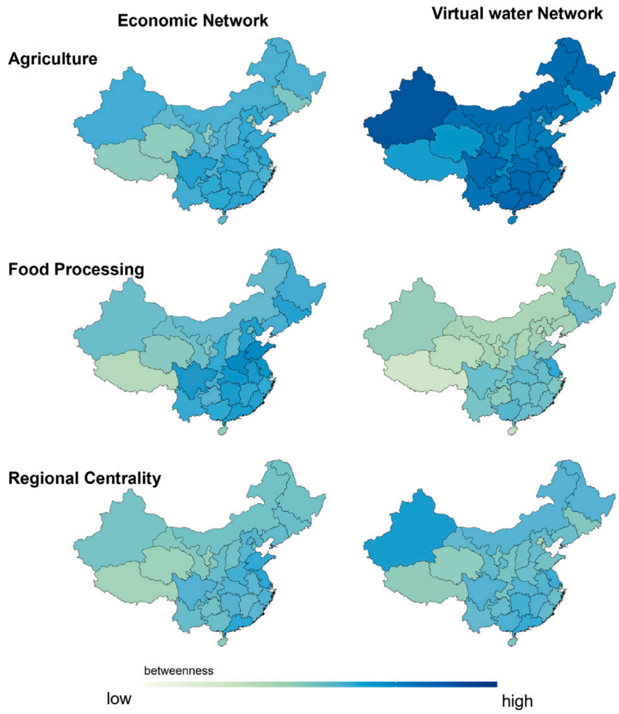

Fig. 6. Betweenness centrality of the (A) economic and (B) virtual water multilayer network. Note that the betweenness centrality of Agriculture and Food Processing is much higher in the virtual water network, which drives differences in regional centrality between economic and virtual water networks, since regional centrality is the mean of betweenness centrality of different layers for each province. This highlights that node centrality estimation is different when economic or virtual water weights are considered.

3.4. Study limitations

There are some uncertainties and limitation in this study. Major uncertainties are introduced during the network construction process. The construction of the MRIO table involves a high degree of sector and spatial aggregation without further distinction between the 31 regions and 41 sectors. For example, the agriculture sectors in the MRIO table correspond to the farming, forestry, animal husbandry and fishery sectors in the environmental matrix, which are aggregated in this project and lead to a loss of details. Hybrid MRIO developed by Ewing et al. (2012), in which the physical value of the primary product can be assigned to the sectors and regions irrespective of the monetary unit flow in standard-MRIO, might be a further improvement (Ewing et al., 2012; Weinzettel et al., 2014; Ye et al., 2022).

Blue water consumption intensities in this project were constructed from several sources (Zhang et al., 2012; Zhang and Anadon, 2013; PWRB, Provincial Water Resources Bureau, 2017) from different years, limited by the data availability. Most of data come from regional and national census data (PWRB, Provincial Water Resources Bureau, 2017), which is subject to reporting errors. Despite these data limitation, the purpose of this work is not specifically to calculate virtual water flows, but rather to compare and contrast the virtual water and economic multilayers. We acknowledge that reducing uncertainties in virtual water calculations is important in accounting studies, but not the main objective of this study.

4. Conclusions

This study consistently compared the economic and virtual water multilayer networks in China. There is a burgeoning literature on economic and virtual water multilayer networks considered in isolation. This paper fills a gap in the literature by consistently evaluating the similarities and differences between economic and virtual water multilayer networks. Both economic and virtual water multilayer networks are highly connected and spatially heterogeneous. Agriculture is the most central sector in China's virtual water multilayer. Virtual water flows to downstream sectors in a lumpy way and does not remain in primary economic sectors, such as agriculture. This suggests that improving the water use efficiency of downstream industries is another way to reduce total supply chain water use. These findings also highlight the province-sectors that are reliant upon agriculture and may be at risk to irrigation water shortages.

Importantly, the central nodes are different between the economic and virtual water networks. This implies that if the study of virtual water network aims to find the important nodes in the network, ignoring the economic network may lead to incorrect core node identification. Our findings suggest that virtual water multilayer networks are relevant to address questions related to water sustainability, scarcity, and hazards in supply chains. However, examining virtual water multilayer networks in isolation may not identify the economically important core nodes. The central node identification can be used by policy makers and managers in future work to determine the location-sectors to invest in to improve domestic supply chains within China. This understanding could also lead to some real application in future study, for example, through the incorporation of both virtual water and economic networks into a multi-objective optimization system aimed to manage the supply chain, where an understanding of the nature of both matrices can help us decide on the definition of the objective function.

This study focused on China, which is a key country in the global trade system. These findings on the relationship between economic and virtual water multilayer networks should be generalizable to other locations and spatial scales. The same approach could be applied to different locations and spatial scales in future work, such as global trade. Additionally, future research could evaluate the time trends of supply chain multilayer network statistical properties to assess their evolution, stability, and resilience. These findings shed light on the relationship between economic and virtual water networks and can help inform future research on supply chains and their embedded resources.

CRediT authorship contribution statement

Junren Wang: Synthesized data, Performed analysis, Created tables and figures, Discussed the results, Contributed to the final manuscript. **Megan Konar:** Obtained funding, Supervised the research, Discussed the results, Contributed to the final manuscript. **Carole Dalin:** Discussed the results, Contributed to the final manuscript. **Yu Liu:** Discussed the results, Contributed to the final manuscript. **Ashlynn S. Stillwell:** Obtained funding, Discussed the results, Contributed to the final manuscript. **Ming Xu:** Discussed the results, Contributed to the final manuscript. **Tingju Zhu:** Obtained funding, Discussed the results, Contributed to the final manuscript.

Declaration of competing interest

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.

Data availability

All data is made available at the DOI: https://doi.org/10.13012/B2IDB-5215221_V1

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jclepro.2022.135041.

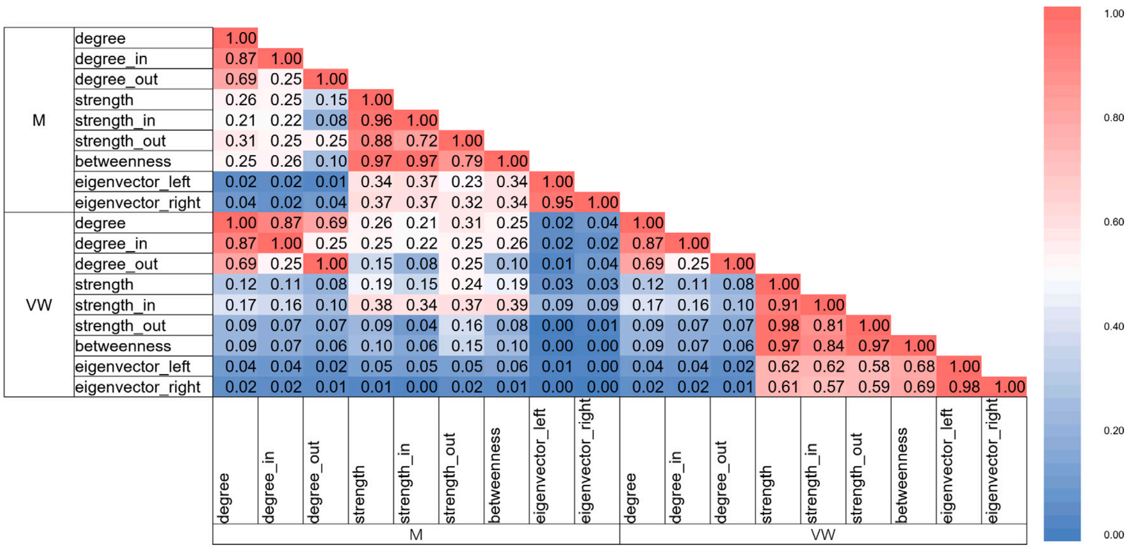

Fig. 7. Heatmap of the correlation in node centrality measures for economic and virtual water multilayer networks.

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