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Analysis of the Global Virtual Water Scarcity Risk Transfer Network Based on Motif

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Abstract: In recent decades, due to climate change, severe drought, population growth and increasing demand, fresh water resources have become scarcer worldwide, resulting in severe water shortages in many regions. However, water stress in a region is not only related to the amount of water in the local water reserve, but can also be alleviated by the virtual water embodied in the trade. In this study, the initial risk of water scarcity describes the possible economic loss of a country or region due to water shortage. Based on the global multi-regional input-output (MRIO) table, the transfer of global virtual water scarcity risk(VWSR) from 1990 to 2016 is quantified, and the global virtual water scarcity risk transfer network (GVWSRTN) is established. And the network is analyzed from the perspective of motif. The results show that the proportion of $M12$, $M4$ and $M7$ in the study period is significantly higher than that of other motifs, and the load capacity index of $M5$ is the highest. It indicates that these motifs are critical path patterns in networks. This work is helpful for the mitigation of water scarcity risks and the development of related strategies.

Keywords: virtual water; scarcity risk; complex network; network motif

1 Introduction

The Earth's water reserves are abundant, totaling 1.45 billion cubic kilometers. Although there is a huge amount of water on the earth, there is very little that can be directly used by people for production and living. The freshwater resources that human beings can really use are part of rivers, lakes and groundwater, accounting for about 0.26% of the total water on Earth [1]. Water is a vital resource, but ensuring its availability faces the challenges of climate extremes and human intervention [2]. In addition, the quality and quantity of water resources are declining due to overuse, climate change and population growth [3]. About 1.5 billion people in 80 countries and territories, representing about 40% of the world's population, are short of fresh water, and about 300 million people in 26 countries are extremely short of water. Even worse, it is estimated that by 2025, 3 billion people in the world will face water shortages, with 40 countries and regions suffering from severe freshwater shortages [1].

The water used in the production process of commodities is called virtual water contained in commodities. International commodity trade brings about the international flow of virtual water [4]. Uneven distribution of water over time and space has led to water crises in many countries, where water-scarce countries may wish to import products that require a lot of water in their production (water-intensive products) and export products or services that require less water (water-intensive products). This means net imports of virtual water (as opposed to actual water imports, which are often too expensive) and will relieve the pressure on the country's own water resources[5]. Virtual water trading has been proposed as a means of balancing national water budgets while also conserving water globally [6]. At present, virtual water is mainly measured by multi-regional input-output tables, which are used in agriculture, industry and other industries. Cao et al. [7] took crop-water relationship estimation in 31 provinces of China as an example and established the VWF influence analysis framework considering the differentiation of blue, green and gray water. D'Odoric et al. [8] discussed the spatial-temporal dynamics, driving factors and effects of global VWT through a comprehensive analysis of surface water, groundwater and root zone soil water consumption. Quantifying the impact of global and regional water resources helps to shape patterns of water dependence through remote linkages between consumers and producers.

Recently, a large number of studies have applied complex network theory to reveal the structure of virtual water risk transfer. Carr et al. [9] used a rich database of international trade to reconstruct a virtual water network from 1986 to

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2008. During this period, total traffic more than doubled and the number of links increased by 92 percent. The study found that the network has become more homogeneous, but most flows are concentrated in a few links and hubs, while some countries have only a few (and weak) links. 50% of global traffic is carried by 1.1% of links, and an average of 6-8% of the global population controls more than 50% of net virtual water exports. The web is very dynamic and intermittent, with only a few permanent links, while many links are created and disbanded each year.

In addition to the global structure perspective, some studies have focused on assessing the importance of nodes, such as degree, intermediate degree and PageRank[10]. Milo et al. [11] proposed the motif concept to study the structure of complex networks from the perspective of the connection mode between several nodes from the local perspective. At present, the research on motif mainly focuses on the recognition algorithm of motif in complex networks, high-order motif and its application in practical networks. A network motif detection is a search for statistically overrepresented subgraphs in a larger target network. They are thought to represent key structures and control mechanisms. Although the problem is exponential in nature, a number of algorithms and tools have been developed to efficiently detect network patterns [12]. Ribeiro et al. [13] proposed a definition of color patterns and used the g-tries algorithm, which is a data structure created specifically to find subatlas to discover them effectively. At present, motif analysis has been widely used in biology, trade, materials and other disciplines. Network motif is statistically an overrepresented substructure (subgraph) in networks and is considered a simple building block for complex networks. Research on motif of biological networks can reveal answers to many important biological questions [14]. Network motif found in human signaling networks has been used to identify breast cancer patients, provides explanations for better understanding of the functional role of certain genes in gene regulation, allows prediction of protein-protein interactions in PPI networks, is used to explain why some recurrent neural networks have good memory performance, and is used to explore the mechanism of response of cervical cancer to epidermal growth factor (EGF) regulatory network and the discovered marker network motif can be used to predict the function of unknown proteins in PPI networks [12]. Network motif has been used to identify network activity [12]. In this application, the network pattern is mapped to the application. The implementation achieves an average accuracy of 85%. Therefore, it improves network resource management and security enforcement [12]. Feng et al. [15] introduced the structural analysis model and combined with the motif analysis model to analyze the structural characteristics of the communication network of pyramid selling organizations from the perspective of microstructure. Xiao et al. [16] proposed a new network moon-based STS support capacity planning method to improve seasonal robustness. This method can be generally applied to other STS whose system performance is greatly affected by seasonal changes, such as supply chain network, transportation system and power grid [16]. In order to make up for the vacancy of complex relationships between various sections of road network, Shen et al. [17] proposed a Motif-based attribute road network clustering method, and conducted a set of experiments on two real-world data sets to prove that the method's performance is superior to existing methods. Hao et al. [18] conducted numerous experiments on real data sets based on motif's complex factor subclass problem memory networks, confirming that the model is significantly superior to the most advanced methods. In order to identify the characteristics and driving forces of interindustry CO_2 emission interaction patterns, Ma et al. [19]studied the interaction pattern types, interaction intensity and key interaction patterns of CO_2 emission flow networks in 28 industries in China during 1997-2015 through network motif analysis.

This study quantifies the transfer of virtual water scarcity risk based on multi-regional input-output tables and water resources data of various countries in the world, establishes a global virtual water scarcity risk transfer network. Based on network motif analysis, the structural characteristics and temporal and spatial evolution of the global virtual water scarcity risk transfer network are investigated.

2 Methods and Data

2.1 Construction of GVWSRTN

Water shortage risk is defined as the potential economic output loss of a sector due to water shortage [20]. Under the background of globalization, the risk of economic loss caused by water shortage can be transferred through economic and trade activities. This study is based on a method to quantify virtual water scarcity risk [21], including initial risk estimation and overall risk transmission.

The probability of water scarcity occurrence can be estimated through the water resources stress Index (WSI) of each country [21] to measure the expected proportion of a country's water consumption reduction due to potential water shortage [22]. The probability of water scarcity occurrence in each country follows a lognormal distribution and is located at [0,1]. The formula is as follows:

$$WP_i = f(\mu_i;\sigma) = \int_0^1 \frac{1-x}{x\sigma\sqrt{2\pi}} \exp(-(\frac{lnx-\mu_i}{\sigma\sqrt{2\pi}})^2)dx, \tag{1}$$

where $\mu_i = log\frac{1}{WSI_i}$[22]. $WSI_i = \frac{\sum WU_i^k}{\sum WA_i^k}$ is the water pressure index of country i, defined as the ratio of annual water consumption and water resource availability in a region, where WU_i^k is the water use of sector k of country i, and WA_i^k is the water availability of sector k of country i [22].

Water resource vulnerability(WV) measures the percentage of sectoral economic output loss caused by a 1% reduction in water consumption [22]:

$$WV_i^k = g(WI_i^k;\alpha) = \frac{1}{1+e^{-\alpha WI_i^k(\frac{1}{0.0001}-1)}}, \tag{2}$$

where water intensity (WI) is used to assess a sector's dependence on water resources; α is the parameter regulating the critical value of WI [23]. WI is the ratio of water consumption to a single economic output, $WI_i^k = \frac{WU_i^k}{x_i^k}$, where x_i^k is the economic output of sector k of country i. The water-using sector faces the risk of being unable to meet its production needs due to water shortage. We quantify the water shortage and the possible economic losses it causes, and call it the initial risk of water scarcity [21]. The initial risk of water scarcity in sector k of country i is evaluated by the multiplication of the probability of water shortage, the sectoral vulnerability to water shortage and the total production of each sector:

$$WPL_i^k = WP_i \times WD_i^k \times x_i^k, \tag{3}$$

where WP_i denotes the occurrence probability of water scarcity, WV_i^k denotes the vulnerability of water resources, and x_i^k denotes the output of sector k of country i.

Environmentally Extended Input-Output (EEIO) model is derived from Leontief's economic input-output model. It is a powerful method to quantitatively analyze the relationship between environmental and ecological elements related to human activities, such as energy, water and CO2, as well as the input-output relationship among component elements [24]. In this study, Ghosh's economic input-output model was adopted to convert the monetary I-O table into physical I-O table, quantitatively analyze the relationship between water and input-output relationship, and build the VWSR model [24]. Global trade between national sectors is described by the global multi-regional input-output (MRIO) model [23]. The MRIO table shows the complex relationship between input and output within countries and between countries at the sector level. The total input of each sector is equal to the sum of intermediate input and value-added of other sectors in all regions, which is shown in matrix format [20]:

$$x = eZ + v, \tag{4}$$

where x represents total input in each sector, v represents value added in each sector, Z represents trade in goods and services between provincial sectors, and e is a $1 \times n$ vector where all elements are 1. The direct output coefficient matrix B is defined as the proportion of product distribution in all sectors of a country [20]:

$$B = (\hat{x})^{-1}Z = (b_{ij}^{pq}) = (\frac{z_{ij}^{pq}}{x_i^q}). \tag{5}$$

Therefore, Eq.(4) can be converted into Eq. (6):

$$x = v(I-B)^{-1}, \tag{6}$$

where $(I-B)^{-1}$ is Ghosh inverse matrix. The elements in one row describe the total (direct and indirect) output of the sector caused by the single value added to the sector shown in this row [23]. Then the impact of initial risk of water scarcity is evaluated by [23]

$$\triangle x = WPL(I-B)^{-1}, \tag{7}$$

where vector $\triangle x$ represents direct and indirect output losses due to water use efficiency in all sectors of the national sector, and vector WPL represents local water scarcity risk in the provincial sector. The matrix $\triangle X$ is obtained by diagonalizing the vector LWSR in Eq. (5). Each row element of the matrix $\triangle X$ represents the output loss of the WPL for each country sector generated by the particular country sector represented by the row,

$$\triangle X = [diag(WPL)](I-B)^{-1}. \tag{8}$$

Suppose there are m countries, N is a $m \times n$ matrix, and the elements n_{ij} represent the influence of the WPL of country i on the output of country j [23], then

$$N = [n_{ij}] = \sum_{\substack{k \in countryi \\ l \in countryj}} \triangle x_{kl} \tag{9}$$

where $\triangle x_{kl}$ is the influence of WPL of national sector k on the output of sector l. A country's virtual water scarcity risk export (represented by $VWSR_i^{ex}$) and a country's virtual water scarcity risk import (represented by $VWSR_i^{in}$) can be calculated as follows [23]:

$$VWSR_i^{ex} = \sum_{i \neq j} n_{ij}, \tag{10}$$

$$VWSR_i^{in} = \sum_{i \neq j} n_{ji}. \tag{11}$$

In order to explore the internal attributes and functional relationships of VWSR between countries and regions, this study adopted complex network analysis method to establish a global virtual water scarcity risk transfer network (GVWS-RTN). In this paper, countries and regions are regarded as nodes, and the flow of virtual water scarcity risk between countries from one country to another is set as an egde. Then, the directed weighted complex network is constructed, as shown in Eq. (12) :

$$G = (N, E), \tag{12}$$

where G represents the global virtual water scarcity risk transfer network; N represents the set of nodes in the network; E represents the side set in the network, and is the transfer amount of virtual water scarcity risk between countries. Based on various water resources indicators and regional input-output tables, this study constructed a global virtual water scarcity risk transfer network from 1990 to 2016 to explore the structural characteristics and interactions among countries. In order to better identify the important links of virtual water scarcity risk transfer between countries, the top 95% of edges sorted by weight are retained in this study.

2.2 Network Motif Analysis

To explore interaction patterns and characteristics of virtual water scarcity risks between countries, it has been proved that most of the topological and dynamic characteristics of various networks come from complex interactions between agents in the network (Barabasi and oltai, 2004). We analyze large real networks from a micro perspective and extract their basic features and implicit information [15]. The microstructure analysis model adopts the motif analysis model [15, 19]. Motif is a basic component of the network and contains important information. A motif is defined as "a significantly higher number of certain interconnected patterns found in complex networks than in random networks". The so-called interconnected mode has 13 possibilities in a directed graph composed of three nodes, as shown in Fig. 1. Each of them can be regarded as a mode if its probability of occurrence in the network is significantly higher than that in the random network. Because of the laws emerging in the process of network generation, the connection patterns that are statistically significant in local areas will cause differences in the global features of the network, which cannot be revealed when only observing the local network. With the introduction of the concept of module, the focus of network research is not limited to the role of nodes or the overall structure of the network, but the micro-structure of the network [11]. To avoid redundant information, only patterns that do not have any isolated nodes are detected. This means that each country in the model has trade flows as a route to and from at least one other country. The distribution of directed links reflects the different interactions between nodes and reveals a variety of information [25].

In this study, Li et al. [26] 's algorithm is combined with traversal algorithm, and R language is used to identify the ternary motifs of the network, and the frequency of motifs' occurrence in the actual network is expressed. In complex networks, there are common local patterns. However, it is hard to say whether these local patterns are random or empirical. Therefore, we further consider the statistical significance of 13 3-node motifs, which implies that local graphs with higher statistical significance are more functional for the evolution of complex networks. According to the basic principles of motif analysis given by Milo [11, 15, 25], z-scores are widely used to measure the statistical significance of patterns. The higher the z-score, the more important the topic. When the z-score is less than or equal to 0, the motif structure fails. The formula can be written as [19]:

$$Z_i = \frac{N_i - (N_{randi})}{\sigma_{randi}}, \tag{13}$$

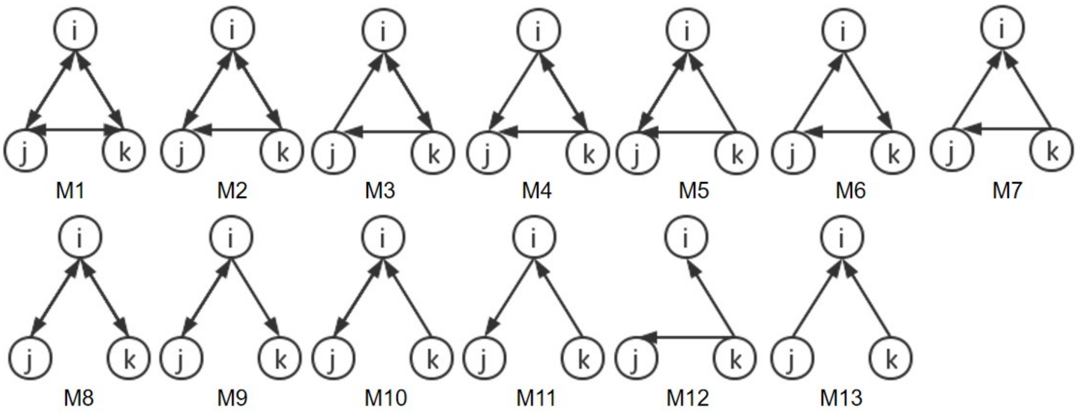


Figure 1: 13 types of directed three-node Motifs, where Mi is an abbreviation for motif i.

where N_i denotes the number of occurrences of motif i in the real world, N_{randi} denotes the number of occurrences of motif i in the random network, (N_{randi}) denotes the mean N_{randi} and σ_{randi} is the standard deviation of N_{randi}.

Most studies only study the degree between motif structures, but ignore the weight of edges in motif. Ma et al. [19] proposed Motif load capacity index to study the role of motif in weighted edge and frequency:

$$LI_i = \frac{L_i}{fr_i}, \tag{14}$$

where L_i denotes the proportion of weighted edges of motif$i$, $L_i = \frac{\sum_{j=1}^{N} sum(E_j)}{\sum_{j=1}^{N} sum(E_q)}$, E_j denotes the weighted edges of subgraph j in motif i; $sum(E_j)$ represents the sum of the weighted edges of subgraph j in motif i, called the carrying capacity of subgraph j; $\sum_{j=1}^{N} sum\,(E_j)$ denotes the sum of the weighted edges of N_i subgraphs in motif i, also called the carrying capacity of motif i; E_q denotes the weighted edges of subgraph q in the real network; $sum(E_q)$ is the sum of the weighted edges of subgraph q in the real network; $\sum_{j=1}^{N} sum\,(E_q)$ is the sum of the weighted edges of N subgraphs in the real network; $fr_i = \frac{N_i}{N}$ is the frequency of motif i, N_i denoting the number of occurrences of base sequence i and N is the number of occurrences of all motifs.The heavier the edge the motif carries, the more functional the motif becomes.

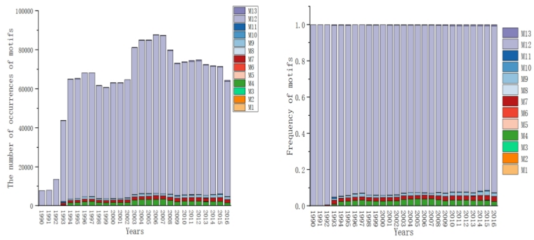
2.3 Data

The implementation of the above method requires multiple data sources, including global MRIO data, water consumption, and water availability in each country. Eora26 database (https://worldmrio.com/eora26/) contains global MRIO water consumption data of sectors of countries and. Global water resources availability data is derived from the FAO AQUASTAT (http://www.fao.org/nr/water/aquastat/data/query/index). Data from 164 countries in two databases were selected for this study.

3 Results

3.1 Motif identification and significance test

In the international virtual water scarcity risk transfer network, the model is the microcosm of the risk transfer relationship. Exploring the microscopic patterns of each country is helpful to further reveal the characteristics of the network. Fig. 3.1 shows the percentage of international virtual water scarcity risk transfer network modules from 1990 to 2016. It can be found that the proportion of $M12$ is significantly higher than other modes, accounting for about 90%, and it is the most common local mode in the international virtual water scarcity risk transfer network. This is followed by $M4$ and $M7$, accounting for about 5% of the total modules. All models showe a small fluctuation trend, indicating that although the network scale increased significantly and more countries participated in the virtual water scarcity risk transfer, the composition of local units is relatively stable. $M12$ shows a local pattern in which the risk of virtual water scarcity in the same country is transferred to two other countries. The local model represented by $M4$ is that a country's virtual water scarcity risk is derived from two countries with bilateral risk transfer relationship. $M7$ reflects the transitivity of virtual water scarcity risk transfer and forms a closed local structure. It can be seen from the proportion of these three modes that one-way outflow relationship is common in the international virtual water scarcity risk transfer network.



(a) The number of occurrences of motifs from 1990 to 2016. (b) Frequency of 13 types of motifs from 1990 to 2016.

Figure 2: Occurrences of motifs in GVWSRTN from 1990 to 2016

In the international virtual water scarcity risk transfer network, each country has some common local patterns. The statistical significance of 13 types of motifs is further discussed below. Motifs with higher statistical significance plays a more important role in the evolution of international virtual water scarcity risk transfer network. According to common rules, the significance of various motifs is described by calculating z-score. A type of motif with z-score>0 is a functional local pattern in the international virtual water scarcity risk transfer network, which has significant empirical characteristics [25]. Table 1 shows seven motifs with statistical significance, which can reflect the evolution of the international virtual water scarcity risk transfer network in the past 27 years. $M12$ has the highest z-score (40.76 on average), indicating that motif had the highest significance in the international virtual water scarcity risk transfer network, followed by $M4$.

Table 1: Significant motifs and their meanings.

	Meaning
$M1$	There is a mutual risk transfer relationship among countries i, j and k
$M2$	There is a mutual risk transfer relationship between country i, j and k respectively, and k outputs risks to j
$M4$	There is a mutual risk transfer between countries i and k, while i and k export risks to j.
$M5$	There is a mutual risk transfer relationship between countries i and j, and country k exports risks to countries i and j simultaneously.
$M7$	Country i imports risks from j and k, while country k exports risks to country j.
$M9$	Countries i and j transfer risks to each other, while i also exports risks to k.
$M12$	Risk of export from country k to countries i and j.

3.2 Interaction strength analysis

In this study, these motifs are further analyzed for their strength. As shown in Fig. 3, the virtual water transfer risk carrying capacity of each motif in GVWSRTN changes with time. Obviously, the LI of $M5$ is much greater than 1 and higher than that of other motifs, which means that $M5$ is the main load-bearing capacity of virtual water scarcity risk between countries, and its function in the network is greatly increased by a factor of 1,000. The LI of other motifs almost tends to 0, and they play an insignificant role in the network. Although $M5$ appeared less frequently, its load capacity index ranked the highest among all motif types despite fluctuations during the study period, and its average virtual water transfer risk reached 9546 in 1994. However, From 1994 to 2003, the virtual water scarcity risk load capacity of $M5$ decreased sharply. Although there is a temporary upward trend, it generally declined and its function decreased correspondingly.

However, the virtual water scarcity risk load capacity of $M5$ increased sharply from 2003 to 2007, and the LI of $M5$ declined sharply after 2008. It shows that the trade between countries in the economic depression decreased due to the impact of the financial crisis in 2008. It shows that $M5$ plays an increasingly large role in the network, and the stronger the incremental effect is, the $M5$ can play thousands of times of its own incremental effect. Although $M12$ has the highest frequency and significance, its carrying capacity is not strong, which indicates that the frequency of occurrence of $M12$ is inconsistent with its role in the risk transfer network. In the process of spreading VWSR, the participation of motif12 is the highest, but its influence is slightly weak. The local pattern of wide distribution between countries may not play a functional role in the evolution of GVWSRTN [19].

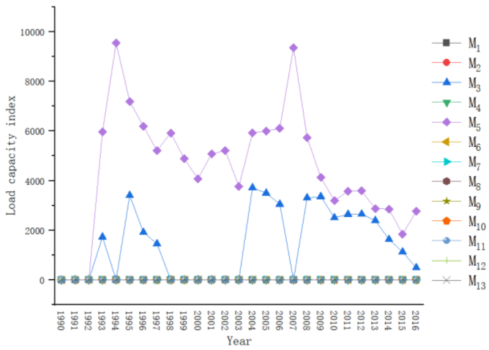


Figure 3: Load capacity of motifs in GVWSRTN from 1990 to 2016.

3.3 Key countries and their roles in motifs

From the perspective of motif, we study the role of countries in GVWSRTN. From the perspective of function, we divide its functions into four types: output, input, transit and reciprocity. From 1993 to 2016, we quantified the degree of export, import, transit and reciprocity in 164 countries and normalized them, selecting the top ten countries as the key countries. Unlike measures of structural roles, such as outflow, inflow, and intermediary centrality, the functional roles of countries are measured by the number of times they appear in certain roles in the GVWSRTN [25]. Fig. 4 shows that there seems to be a great deal of similarity and overlap between the Top countries playing different functional roles. China, the US, India and several European countries play an important structural role in the GVWSRTN, whether exporters, importers or conveyancers. As can be seen from Fig. 3.3, USA has played the role of exporting country since 1993 and ranked first almost every year from 1993 to 2016, indicating that it is the main party transferring virtual water scarcity risks and exporting risks to other countries. China gradually rose in the ranking since 1993 and remained at the second place in 2008, indicating that China's rapid economic development, gradually developed economy and trade, and exported risks to other countries. Germany was in the top two until 2000, when China overtook it. France,Japan,Italy90's output VWSR more, after reduced twists and turns, but still in the Top10 ranks of output functions. As can be seen from Fig. 3.3, during the study period, VWSR imported from different countries were roughly the same, with slight differences in quantity but the same trend. As can be seen from Fig. 3.3, over time, Germany, France and China rank top among transit trade countries, similar to the ranking of reciprocity, indicating that these three countries have close trade links with other countries and are trade hubs for other countries, among which Britain, the United States, Italy and Japan are also major risk transfer transit countries. As can be seen from Fig. 3.3, Germany and France are the largest transit countries and reciprocal countries, accounting for 21.56% and 13.47% respectively on average, indicating a high degree of trade interaction between them and other countries. Therefore, the functional role of the state revealed in the report provides a new perspective for measuring national contributions [25].

4 Conclusions

Based on motif analysis of international virtual water scarcity risk transfer network, it can be found that $M12$, $M4$ and $M7$ occupy significantly higher proportions than other motifs during 1990-2016 with high significance, indicating that these three Motifs are important structures. In the global virtual water scarcity risk transfer network, there are mainly

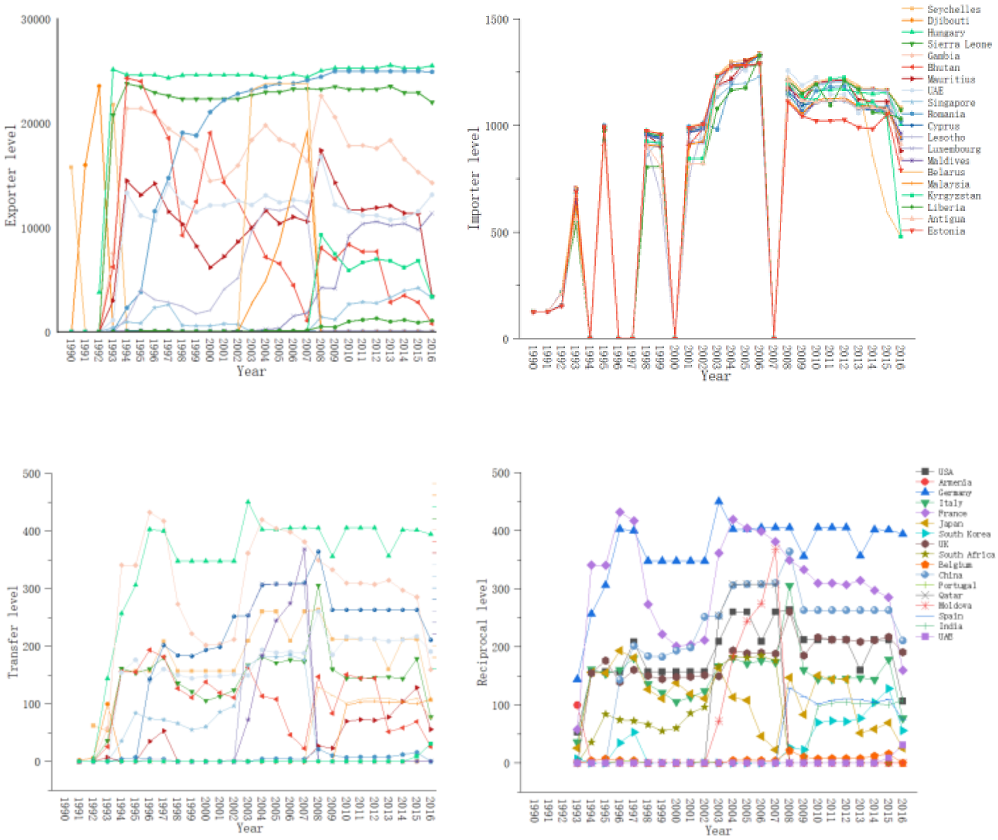


Figure 4: Exporter(a), importer(b), transfer(c) and reciprocal(d) level of key countries in motifs in GVWSRTN from 1990 to 2016.

three local modes: one country transfers risk to other two countries, one country transfers risk to another country through a third country, and two countries with mutual transfer relationship transfer risk to another country at the same time. Among these three local patterns, $M12$ accounts for the majority. This is consistent with the global structure of a small number of high virtual water scarcity risk transfer countries to all countries in the world. In weighted network motif analysis, the load capacity index of $M5$ was the highest among all significant motifs. In this motif, a country not only has a mutual relationship with another country, but also can transfer risks to it through a third country, and carries a high transfer risk in this interaction mode. It indicates that $M5$ has a strong influence in the process of spreading VWSR although its participation is not the highest. During the study period, China, the United States, India and several European countries played an important structural role in GVWSRTN, mainly as major exporting countries of virtual water scarcity risk, dominating the majority of the world's virtual water scarcity risk transfer volume. However, the difference of virtual water scarcity risk between countries is small and stable during the study period. The conclusion obtained from the perspective of network motif analysis is consistent with that from the perspective of degree. Germany, France, China, the United Kingdom, the United States, Italy and Japan have a higher transfer level and close trade links with other countries. They are the trade hubs of other countries, which is consistent with the conclusion derived from centrality.

Network motif analysis helps to identify key countries and critical pathways in the global virtual water scarcity risk transfer network and provides valuable information for water managers and policy makers in mitigating water scarcity risks.

Acknowledgments

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