Rainfall patterns in the East Asian 24 mega-cities using a complex network

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Abstract. Concurrent floods in multiple locations pose systemic risks to the interconnected economy in East Asia through supply chains. Despite the significant economic impacts, the understanding of the interconnection between rainfall patterns in the region is yet limited. Here, we analyzed spatial dependence in rainfall patterns of the 24 mega-cities in the region using complex analysis theory and discussed the technique's applicability. Each city and correlation coefficient was represented by a node and a link, respectively. Vital node identification and clustering analysis were conducted using adjacency information entropy and multi-community detection. The groups were clustered to reflect the spatial characteristics of climate. In addition, the climate links between each group were identified through the cross-mutual information considering the delay time for each group. We conclude that complex network analysis could be a valuable method for analyzing the spatial relationship between climate factors.
Keywords: Concurrent floods, Complex network, Adjacency information entropy, Multi-community detection

1 Introduction

East Asia accounts for 54% of the global supply chain, providing a wide range of services and products across the world (Ann et al, 2020). However, East Asia is prone to major floods. According to disaster database of the Centre for Research on the Epidemiology of Disasters (CRED), which offer essential core data on the occurrence and effects of disasters all over the world, an annual average of 165 flood disasters occurred worldwide during 2000 to 2020, resulting in 5,278 deaths and economic damage up to $29 million. While more than 22% of these flood disasters have occurred in East Asia, more than 60% of global-flood deaths and economic damage worldwide are in the region. For instance, Thailand recorded 813 deaths and $40 million worth of damages from floods in 2011 (Haraguchi and Lall, 2015), while China recorded 300 fatalities and $4.5 million in damages from floods in 2019 (CRED). These flood damages occurred in several areas of East Asia simultaneously. Even though floods occurred simultaneously at distant places, the impacts of floods will propagate through supply chains, incurring economic losses in the entire region. In this sense, concurrent flooding causes severe life and economic losses in multiple countries at the same time, disrupting the global economy more severely. For example, in 2020, concurrent floods in East Asia inundated automobile factories in Thailand, disrupting automobile supply, adversely affecting China's rare-earth and fertilizer industries along the Yangtze river, and affecting the global rare-earth industry (AON. 2020).

Changes in rainfall characteristics caused by climate change are some of the primary causes of concurrent floods in East Asia. These changes occur across all regions, and the changed characteristics affect each other, resulting in even more significant changes (Wang et al., 2020). Therefore, it is vital to investigate the relationships among rainfall patterns in each region. Many studies have been conducted to identify rainfall relations in East Asia. Most of them investigated the relationship between major East Asian countries using statistical techniques (Jeong et al., 2008, Kosaka et al., 2011, Deng et al., 2014), and some demonstrated connections among weather factors, sea-level temperature, and monsoons. (Wu et al., 2003, Lau and Kim., 2006, Li et al., 2010, Sun and Wang, 2012, Renguan, 2017). Researchers have also used teleconnection methods to discover

relationships between precipitation in East Asia and other parts of the world (Kripalani and Kulkarni, 2001, Sahai et al., 2003, Riyu and Zhongda, 2009, Lin, 2014, Maity et al., 2020.). These studies have been used to anticipate rainfall in East Asia and aid in preparing for flood disasters. This study investigated the usefulness of complex network concepts for relationship analysis.

45   Complex network theory, developed by Leonard Eüler in 1735, expresses and analyzes a subject or phenomenon as a graph. In the late 1990s, Watts and Strogatz (1998) and Barabási and Albert (1999) extended the analytical technique, making the theory fundamental in network science. A complex network can display a complicated phenomenon as a simple graph. Information obtained from the methodology can be used to identify the characteristics of subjects, their physical behavior, and the roles and relationships of the phenomenon's components. Complex network analysis has also been used in various fields

50   because of its high applicability. For example, researchers have applied it to social networks (Michael et al., 2010), world trade (Bader et al., 2007), air transportation nets (Cardillo et al., 2013), patterns in human migration (Davis et al., 2013), and others. The analytical method has also been used in the fields of hydrology and meteorology fields to discover new patterns and relationships (Donges et al., 2009, Scarsoglio et al., 2013, Boers et al., 2015, Joo et al., 2021, Wolf et al., 2020). About precipitation related researches, the method had been used to analyze extreme rainfall patterns around the world (Boers et al.,

55   2019), track rainfall events caused by typhoons (Ozturk et al., 2018), and study the spatial connectivity of rainfall (Ihsan et al., 2018) to determine new information or characteristics.

With the encouraging results of previous rainfall-related studies, this study applied complex network theory to rainfall in East Asia to understand the relationships between the rainfall patterns in each region. A complex network defines connectivity using correlation methods. Therefore, characteristics can be analyzed from the relationships. In addition, for clustering analysis,

60   complex network-based methods consider the entire network, rather than the regions independently, unlike many other traditional methods. This feature results in a more accurate clustering (Long and Liu et al., 2019). Despite this advantage, one of the challenges in complex network theory is to identify thresholds, which determines whether the links existed. While no perfect methodology exists to clearly address this challenge, new methodologies are constantly being proposed. In this study, we assumed that each region (node) is connected with all the other regions (nodes) in the network, and that each connection

65   (link) has a correlation coefficient as a weight. Using the correlation coefficient makes that a network reflect relationship between region. The link weight is one of the most important input for constructing and analyzing a network. We assessed the effects of each region through centrality analysis and grouped the regions according to clustering analysis. Subsequently, Mutual Information (MI) was calculated with a time lag (i.e., cross-mutual information) to identify the relationships between each group. Past studies about complex network considered only spatial factors, while we add also temporal factors.

70   The remainder of this paper is organized as follows. Section 2 describes the study area and data used in this study. The complex network theory and related indicators are detailed in Section 3. Section 4 presents the results of the complex network analysis of East Asia and a discussion of these results. Section 5 presents the conclusions of this study.

2 Study area and materials

In this research, the major cities in East Asia are analyzed (Fig. 1). Among East Asia cities, we used selected cities selected

75   by Haraguchi et al. (2019). They chose the cities with more than 5 million people and a high degree of urbanization. Because, rainfall often causes numerous floods in the region, and with growing urbanization, more and more cities suffer from small and medium-sized frequent floods, as well as large scale low-probability floods (The World Bank, 2015). However, we excluded Surabaya, Jakarta, and Badung (Indonesia) from the selected cities because of the changes in the location of rainfall observation since 2007. Instead, we included Ho Chi Minh City, Hai Phong (Vietnam), and Cebu (Philippines), which are

80   economically emerging. Thus, a total of 24 cities were selected.

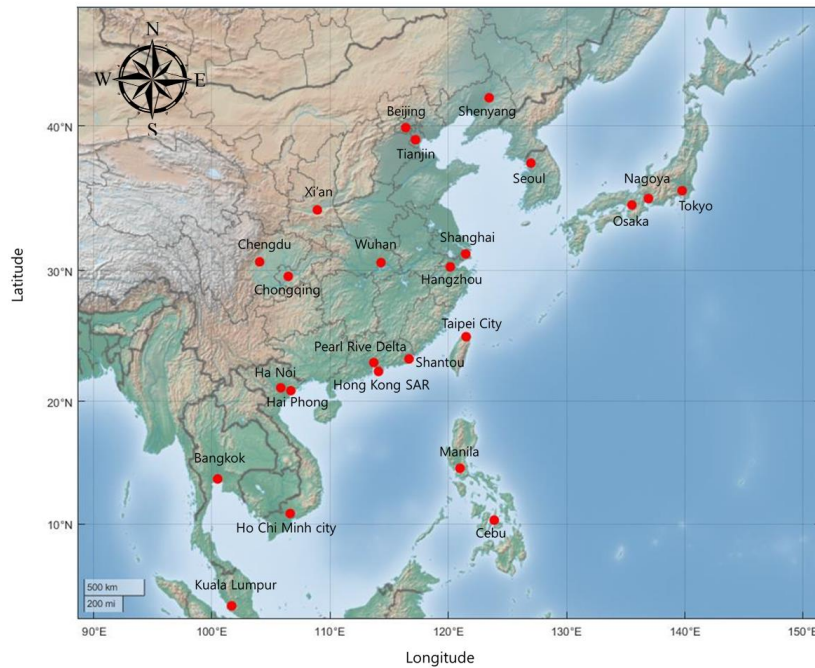



Figure 1. Selected 24 major cities in East Asia

   This study used daily precipitation data from the Asian Precipitation – Highly Resolved Observational Data Integration Toward Evaluation (APHRODITE) grid precipitation dataset (Akiyo et al., 2012). The APHRODITE data contains long-term,
85   high-resolution daily rainfall data of the Asian continent obtained from the dense precipitation observation data network (Fig. 2). The data were obtained from the APHRODITE Water Resource project conducted by the Research Institute for Humanity and Nature (RHIN) and the Meteorological Research Institute of Japan Meteorological Agency (MRI/JMA) and have been used in many studies because of their high definition.

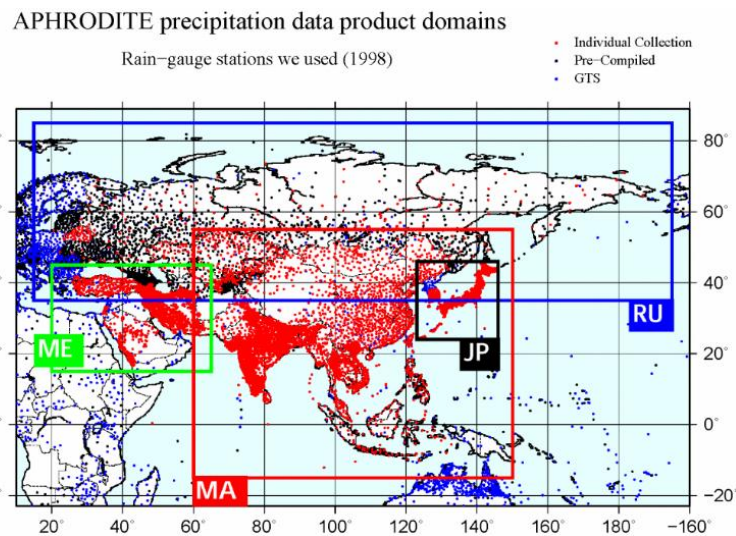



Figure 2. APHRODITE data (http://aphrodite.st.hirosaki-u.ac.jp/products.html) of cities; Dots are example of station data distribution that were used for making data(Red: individual collections, Black: pre-complied data, Blue: global telecommunication networks (GTS) based data obtained from Global summary of day (NCEI/NOAA)). Rectangles show the domain of precipitation data. In this research, precipitation data on a 0.25 degree grid for Monsoon Asia (MA) for the period from 1981 to 2015.

95   Daily rainfall data for each city consisted of observations from January 1, 1981, to December 31, 2015. The basic statistics for each city's rainfall data are the same as those listed in Table 1.

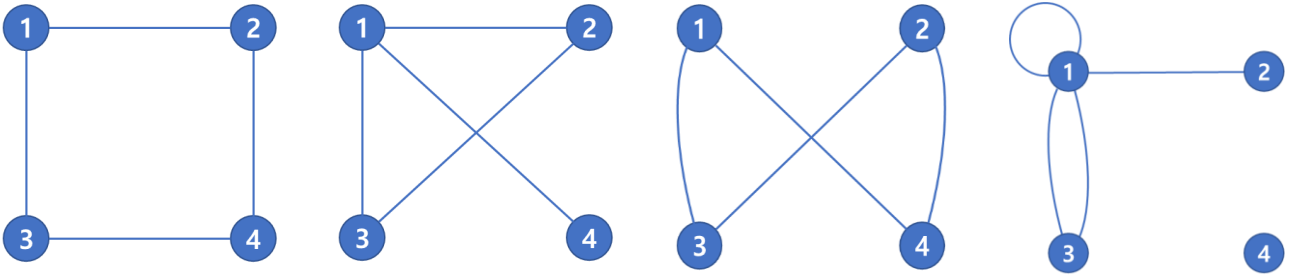
Table 1. Basic statistics values for rainfall data of cities; Basic statistics contain average, standard deviation, coefficient of variation and skewness.

Station	Average (mm/day)	Standard deviation	Coefficient of Variation	Skewness
Pearl River Delta	4.277	9.416	2.202	4.063
Tokyo	3.637	10.736	2.952	7.044
Shanghai	2.985	6.446	2.160	3.993
Beijing	1.316	4.377	3.325	6.395
Manila	6.241	12.514	2.005	5.023
Seoul	3.457	9.427	2.727	5.543
Osaka	2.802	5.900	2.105	4.619
Bangkok	1.101	4.067	3.694	7.308
Tianjin	3.903	9.932	2.544	4.910
Shantou	2.211	4.853	2.195	5.279
Chengdu	3.782	6.241	1.650	3.246
Ho Chi Minh City	4.551	11.314	2.486	4.919
Nagoya	3.176	7.762	2.444	4.492
Wuhan	4.583	11.278	2.461	4.427
Hong Kong SAR	4.889	6.460	1.321	2.177
Shenyang	1.590	4.946	3.11	6.183
Taipei	6.955	16.128	2.319	6.192
Hangzhou	3.614	7.413	2.051	3.981
Kuala Lumpur	6.196	7.970	1.286	2.311
Xi'an	1.527	4.099	2.684	5.054
Ha Noi	4.053	8.870	2.189	4.417
Chongqing	2.790	5.751	2.061	4.890
Cebu	4.126	6.759	1.638	4.923
Hai Phong	3.801	9.530	2.507	5.023

100   Taipei records the largest rainfall amount on average, approximately six times more than that of Bangkok, which has the lowest. Bangkok has the largest variation, and Kula Lumpur has the least.

3 Methodologies

3.1 Complex network analysis

Complex network analysis effectively visualizes a subject or phenomenon using a network and analyzes its characteristics,
105   components, and relationships among nodes in the network. To apply complex network analysis, nodes and links must be defined. A node is a fixed element that serves as a point of intersection/junction within a network. For example, in the global airways network, airports become nodes. A link is an element that connects each node. In a global airways network, airways are the links. Defining these two elements is crucial in the analysis because even networks with the same number of nodes and links can potentially makes various forms (Fig. 3).

110 **Figure 3.** Various shapes of networks with the same number of nodes and links; Each network has 4 nodes and 4 links. However, those shows different shapes and have different topological characteristics.

In a complex network, links are the most influential aspects of the network. This is because the type and characteristics of the graph vary depending on the type of link used and how it is defined. Based on the directionality and weight of the link, the network can be an undirected/directed network or an unweighted/weighted network. Generally, it is easy to define links in

115 transportation systems or power grid system, which show clear connections between elements. However, if uncertainty occurs in the connections like social networks, researchers must define them. The most widely used methodology is the correlation coefficient (Donges et al., 2009). Depending on the value of the correlation calculated between two nodes, the researcher can define whether a link exists. While various previous studies used the Pearson correlation coefficient for links, they tend to derive inaccurate values when they are applied to nonlinear data (Zadian et al., 2018). To address this problem, some

120 researchers have utilized MI as an alternative (e.g., Donges et al., 2009, Kim et al., 2019, Ghorbani et al., 2021). MI is based on the information and probability theory. For two variables (A and B), it quantifies and represents the amount of information of B contained by the variable A.

$$\text{MI}(A, B) = \sum_{b \in B} \sum_{a \in A} p(a, b) log(\frac{p(a, b)}{p(a)p(b)}) \tag{1}$$

Here, $p(a)$ and $p(b)$ are probability distributions of variables. $p(a, b)$ indicates the joint probability density function of the variables. MI values range from 0 to ∞, and an MI of 0 indicates that the two variables are independent of each other. MI can

125 consider the nonlinearity of the data and has the advantage of calculating the correlation between different data sizes (Goyal, 2014).

3.2 Vital node identification using adjacency information entropy

Important nodes in a network have various effects on the structure or function of the network. Identifying these nodes is of practical and theoretical value (Xu et al., 2020). For example, if a government identifies which places have a key role in power

130 grids and traffic networks, it can effectively invest and create defense measures to prepare for blackouts and traffic jams. While some methods of identifying important nodes have been developed, these methods have limitations and are only applicable to certain types of networks (Mester et al., 2021) such as undirected network. Xu et al. (2020) developed a new methodology based on information entropy, making it applicable to all types of networks. This method has more efficient and accurate results than the existing methods. The procedure of the method is as follows (more detailed explanation about the Vital node

135 identification method is in Xu et al. (2020)):

First. Calculate strength(k_i) of each node in a weighted network

$$k_i = \sum_{j \in \Gamma_i} w_{ji} \tag{2}$$

Here, j is the neighbor of node i. Γ_i is the set of neighbors of node i. w_{ji} is weight of link that connect node j and node i. If a network is unweighted, degree is the number of neighbor nodes.

Second, calculate the adjacency degree (A_i) of each node.

$$A_i = \sum_{j \in \Gamma_i} k_j \tag{3}$$

140 A_i is total weight of neighbor nodes of node i.

Third, calculate the selection probability (P_{i_j}).

$$P_{i_j} = k_i/A_j \tag{4}$$

Final, calculate the adjacency information entropy (E_i).

$$E_i = \sum_{j \in \Gamma_j} (P_{i_j} log_2 P_{i_j}) \tag{5}$$

After comparing the calculated adjacency information entropy of each node, the importance is determined according to the descending power.

3.3 Multiresolution community detection in weighted complex networks

A complex network consists of many nodes and links. Some nodes with strong relationships or similar characteristics can be clustered together. These clusters have several features and perform specific network functions. However, the cluster results depend on the level of analysis. Therefore, the multi-resolution community detection method can be a useful method for understanding complex networks (Newman, 2012). Several cluster analysis methods have been used for complex networks, but they require intense computations for complicated network shapes and focus only on graphical properties (Long and Liu, 2019). To address these problems, Long and Liu (2019) proposed a new clustering methodology using an intensity-based community detection algorithm (ICDA) in weighted networks. The procedure for the proposed method is as follows.

First, Define a Distinct path

The simple(not repeating links between nodes) and elementary (not repeating nodes) path θ between node i and j with k-edges is denoted as a k-edge distinct path, if the path has no identical intermediate nodes or edges with any other distinct paths.

Second, calculate the link intensity (I_P) of each link.

$$I_P(e_{ij}) = \sum_{p=1}^{P} \alpha_p \times \frac{\sigma(path_p(v_i, v_j))}{\min(w_i, w_j)}, \quad e_{ij} \in E \atop 0, \qquad\qquad otherwise \tag{6}$$

Here, $\sigma(path_p(v_i, v_j))$ is the sum of link weights in p-edge distinct paths from node i (v_i) to node j (v_j). P is the parameter of the path, and α_p is a polygonal effect parameter. For edge e_{ij} between node i and node j, w_i and w_j are their respective strengths.

Third, identify the links with link intensity greater than the selected threshold and create a group of nodes with the identified links.

$$\begin{aligned} v_j \in V, & \quad I_P(e_{ij}) > t \\ v_j \in c_u, & \quad I_P(e_{ij}) > t \end{aligned} \tag{7}$$

Here, t ($0 < t \le 1$) is the selected threshold, and c_u is a group of nodes.

Fourth, calculate the belonging coefficient (I_P) of the nodes in node set u (c_u).

$$I_P(c_u, v_j) = \sum_{v_i \in c_u} I_P(e_{ij}) \tag{8}$$

This method has the advantages of forming groups more accurately and faster than other methods.

4 Application and Results

4.1 Construction of East Asia rainfall network

In this research, we design a rainfall network as a weighted and undirected graph. Each node was selected from 24 major cities, and link weights represented shared knowledge between nodes. Each node has different link weights. Table 2 compares the results of the link weights of the nodes.

Table 2. Average, maximum, and minimum link weights of each node; Parentheses next to link weights are nodes that form a maximum or minimum value for target nodes;

Node	Average	Maximum (Node)	Minimum (Node)
Pearl River Delta	0.352	1.674 (Hong Kong SAR)	0.203 (Tokyo)
Tokyo	0.226	0.528 (Nagoya)	0.140 (Tianjin)
Shanghai	0.253	1.076 (Hangzhou)	0.153 (Tokyo)
Beijing	0.232	0.850 (Tianjin)	0.130 (Osaka)
Manila	0.294	0.467 (Ho Chi Minh City)	0.219 (Shanghai)
Seoul	0.227	0.276 (Ha Noi)	0.155 (Tokyo)
Osaka	0.244	0.870 (Nagoya)	0.130 (Beijing)
Bangkok	0.272	0.520 (Ho Chi Minh City)	0.194 (Shanghai)
Tianjin	0.252	0.850 (Beijing)	0.143 (Osaka)
Shantou	0.284	0.861 (Hong Kong	0.183 (Beijing)
Chengdu	0.293	0.621 (Chongqing)	0.200 (Shanghai)
Ho Chi Minh City	0.308	0.520 (Bangkok)	0.217 (Shanghai)
Nagoya	0.254	0.870 (Osaka)	0.139 (Beijing)
Wuhan	0.292	0.529 (Hangzhou)	0.195 (Taipei City)
Hong Kong SAR	0.364	1.674 (Pearl River Delta)	0.215 (Tokyo)
Shenyang	0.240	0.367 (Tianjin)	0.166 (Tokyo)
Taipei	0.220	0.333 (Shantou)	0.147 (Beijing)
Hangzhou	0.279	1.076 (Shanghai)	0.164 (Beijing)
Kuala Lumpur	0.308	0.377 (Wuhan)	0.207 (Beijing)
Xi'an	0.271	0.508 (Chengdu)	0.188 (Osaka)
Ha Noi	0.341	1.162 (Hai Phong)	0.238 (Tokyo)
Chongqing	0.289	0.621 (Chengdu)	0.207 (Beijing)
Cebu	0.246	0.354 (Manila)	0.179 (Beijing)
Hai Phong	0.342	1.162 (Ha Noi)	0.235 (Shanghai)

According to Table 2, the ranges of average, maximum, and minimum link weights are 0.22–0.37, 0.27–1.67, and 0.13–0.24, respectively. The average and minimum values have a narrow range, whereas the maximum values have a relatively wide range. We observe that the cities with the maximum values for each node were closely located. This is because rainfall characteristics in cities located in near areas are similar; thus, the value of the MI is high. Each node has a maximum value with several different cities, while the minimum value is for certain cities such as Beijing and Tokyo. Beijing and Tokyo are selected as the cities with the lowest MI value eight and six times, respectively. Two cities have a common feature that their location is in the outskirt of the study area.

4.2 Vital node identification by adjacency information entropy

For the network, we apply Vital Node Identification (VNI) to determine the influence of nodes. VNI can be used to analyze all types of networks and more precisely determine the effects of nodes more accurately. The cities with high ranking nodes are located around the South China Sea (Fig. 4). In addition, they have a large average of MI. Cities with low-rank nodes are in the northeast outskirts, except for Taipei, and have a low mean of MI. From these results, we can deduce that the location of a node affects its influence. High-ranking nodes are in the center of the map and have many neighboring nodes. The characteristics of low-ranking nodes are diametrically opposed to those of high-ranking nodes. However, location is not the

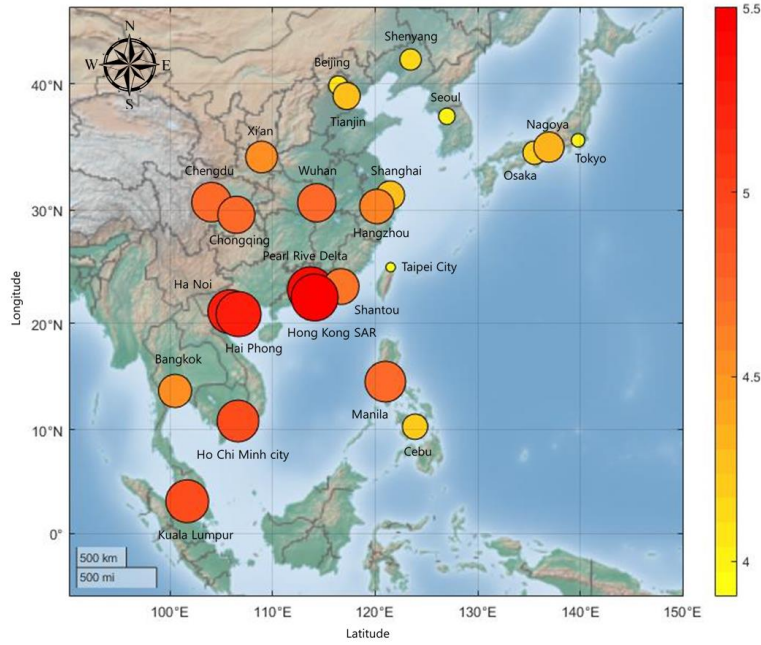
only factor affecting vital node identification. Despite its proximity to the South China Sea, Taipei has a low rank because its link weight is the smallest on average (0.220).

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Figure 4. Adjacency information entropy value of cities; color and size of circle are respectively proportional to the entropy and rank. The right side of bar shows the adjacency information entropy values of nodes; except for Taipei city, nodes near the South China Sea, which had higher values;

4.3 Clustering analysis using multiresolution community detection

195   In clustering analysis, multiresolution community detection is applied to 24 nodes to create groups. After calculating the belonging coefficient, we determine the groups based on the threshold value. The threshold value is the 95th quantile of the calculated belonging coefficient, 0.06, in order to form a group of nodes with strong relationship.
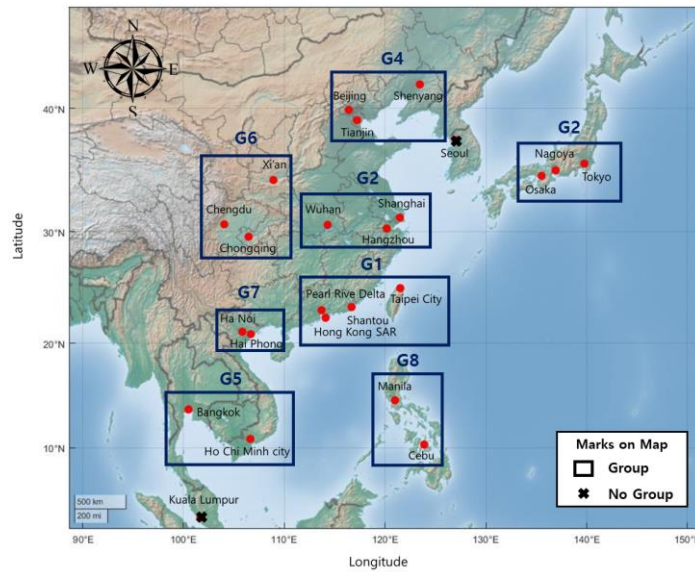
Figure 5. Group of nodes using multiresolution community detection; there are 8 groups in the East Asia; G1(Pearl River Delta, Hong Kong
200   SAR, Shantou, Taipei City), G2(Osaka, Nagoya, Tokyo), G3(Wuhan, Hangzhou, Shanghai), G4(Tianjin, Shenyang, Beijing), G5(Bangkok, Ho Chi Minh City), G6(Xi'an, Chengdu, Chongqing), G7(Hanoi, Haiphong), G8(Manila, Cebu); Seoul and Kuala Lumpur did not make group with other nodes.

Nodes in close proximity form a group (Fig. 5). The cities of Seoul (South Korea) and Kuala Lumpur (Malaysia) are not clustered with the others. Seoul has low belonging coefficients with the nearby nodes because of its location in the Korean

205 peninsula. The area is influenced by maritime air mass in summer and continental air mass in winter. Therefore, the precipitation of Seoul is affected by both features and has different characteristics. This feature makes Seoul distinguish between G2 and G4. For the Kuala Lumpur node, the belonging coefficients calculated with other nodes are between 0.03 and 0.05. Unlike other cities, Kuala Lumpur gets significantly influenced by the Boreal winter season and Australia Summer monsoon (Sigh and Xiaosheng, 2020). Therefore, Kuala Lumpur has a different rainfall pattern, and it makes lower results in

210 the belonging coefficient.

4.4 Relationship between node groups

Nodes are grouped based on their belonging coefficients (Section 4.3). The relationships between the groups are determined using cross-mutual information analysis. Cross-mutual information is a methodology for calculating MI by adding time lags between targets. It can estimate an appropriate correlation coefficient by considering the time intervals for geographically

215 distant points. In this study, the time lag ranges from −10 to 10 days, and we check the maximum cross-mutual information value and corresponding time lag of each group.
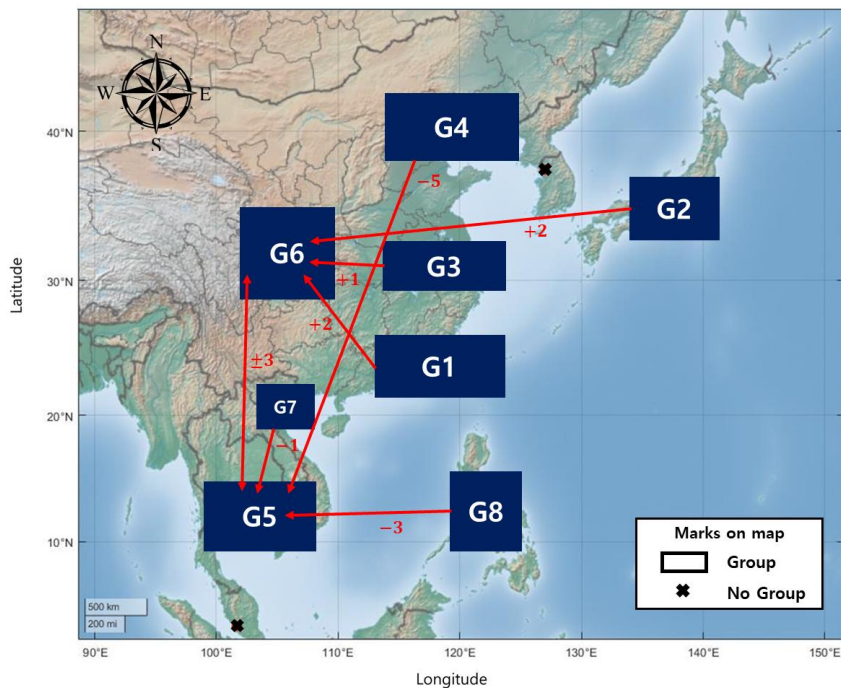
Figure 6. The maximum cross mutual information relationship and its time lag value; each arrow points out the maximum relationship group and the numbers under the arrows express the lag time(days) of the maximum cross mutual information value; the figure shows

220 relationship of groups and influence time intervals in East Asia;

As Figure 6 shows, most groups have strong relationships with G5 or G6 with maximum cross-mutual information values. G5 and G6 have a maximum cross-mutual information value with each other, and this value is larger than other cross-mutual information results. This result indicates that the two regions have a comparatively high relationship. A comparison of the lag

225 times that forms the maximum cross-mutual information indicated that the maximum values are in an interval of fewer than five days. Therefore, East Asian regions can meaningfully relate to each other in a window of five days. The relationships in figure 6 are derived from synoptic atmospheric circulation in East Asia. Indian and East Asian monsoons are major factors affecting rainfall in East Asia. The Indian monsoon brings the highly humid wind from the sea that conveys a large quantity

of vapor across India and the Bay of Bengal to East Asia. This can reach the northern part of China (Wu, 2017). If the Indian monsoon is strong, a large amount of rainfall can occur in India and northern China. This characteristic is observed in the relationship between G5 and G4 (G5 is the first place affected by the Indian monsoon in East Asia, and G4 is the one in northern China). The Indian monsoon moves northwest from the Bay of Bengal, passing mainland China into the Sea of Okhotsk, which is located between the Russia's Kamchatka peninsula and Japan's island of Sakhalin. G5, G6, and G7 in this pathway are related to each other by the Indian monsoon. The effect of the South China Sea, which supplies vapor to the mainland, is due to the relationship between G1 and G6. In the summer, the South China Sea vapor causes much rainfall in southern China and arrives in the mainland (Kanaly et al., 1996). Like the Indian Monsoon, the East Asian monsoon affects East Asian rainfall. The East Asian monsoon begins in the Western Pacific, moves eastward through Indonesia, and ends in Japan and South Korea. If it is strong, it affects southern Vietnam and Thailand (Rehe and Akimasa, 2002). This is observed in the relationship between G8 and G5. In the summer, there is an anomalous anticyclone between China and Korea. The anomalous anticyclone locates in the western sea forms a clockwise wind cycle throughout China, Korea, and Japan (Rengquang, 2017). This creates a wind cycle that transports vapor from Japan to the east and the center of China. This phenomenon forms relationships between G2 and G6 and between G3 and G6.
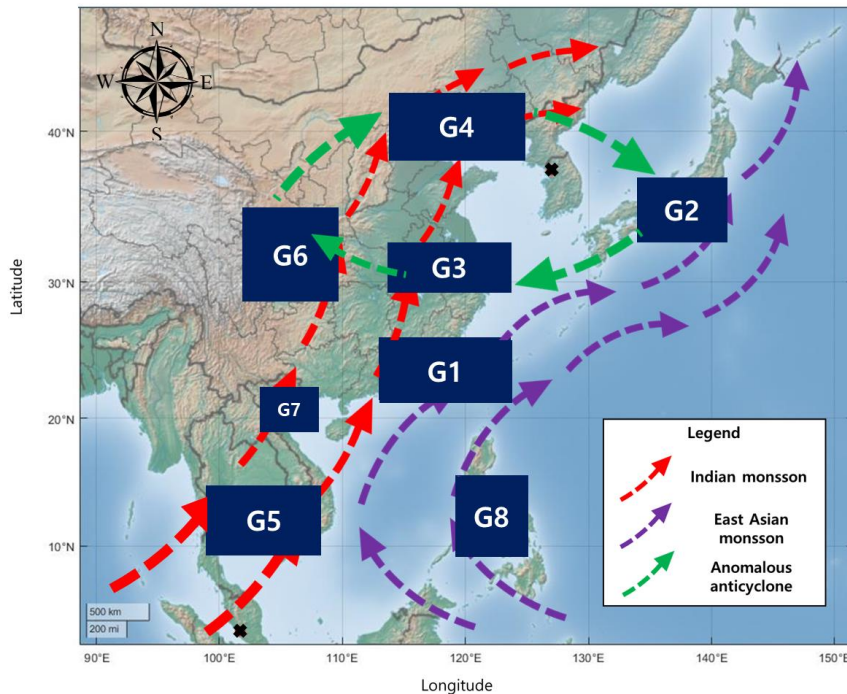
Figure 7. Major water vapor transport routes in East Asia; the routes could explain the reasons why the relationship of groups was made like Figure 6; Indian monsoon brings vapor from Indian Ocean, East Asian monsoon gets vapor from Pacific Ocean and east china sea; Anomalous anticyclone provide vapor in east china, Korea and Japan;

4.5 Discussion

Complex network analysis has the advantages of reducing complex phenomena or systems to a graph form, making it easier to determine characteristics. In addition, it can be used to analyze the effects of network components, perform clustering analysis. Given these merits, we used complex network analysis to examine the relationships between major cities in East Asia.

To create a rainfall network, we first calculate the MI between nodes and use it as the link's weight. Thus, the network can reflect the correlation of rainfall in each city and is used as the most important factor in subsequent analyses. In the mutual information result, we could find that many cities had the lowest value with Tokyo and Beijing. We tried to find why this result came out, but we could not find any differences in the rainfall data. Therefore, future studies should collect and analyze other

climate and geographical factors to discover unique rainfall characteristics in Tokyo and Beijing. The adjacency information entropy was calculated and compared to check the effects of nodes in the network. The results indicate that nodes surrounding the South China Sea were highly ranked, and the node's location is one of the essential factors in identifying vital nodes. The South China Sea is one of the primary vapour providers in East Asia, and the two significant monsoons pass through it. Vapour from the South China Sea first affects coastal cities and then moves to other cities in the continent. Thus, rainfall from some cities affects the neighbouring cities. Based on this phenomenon, cities in the South China Sea ranked high.

As described in Section 4.3, the coefficient of each node was calculated by using the link weight. Each group consists of nodes located nearby, and their coefficients are significantly higher than those of the other nodes. After clustering, we apply cross-mutual information analysis to determine the relationships between groups. During the analysis, the lag time is considered because the groups are geographically separated. The cross-mutual information results are interpreted using the rainfall characteristics of East Asia. Two monsoons (Indian and East Asian monsoons) and anomalous anticyclones affect group relationships. An intriguing result is the strong relationship between G5 and G6. Even with G7 between them, they have a strong correlation. Previous research has primarily focused on the relationship between southern China (G1) and regions surrounding the East China Sea (G5, G7, and G8) (Yuan and Qie, 2008, Hu et al., 2014, Zhao et al., 2017). These studies analyzed the effects of monsoons in the East China Sea but did not expand the region to G6. Therefore, research into the physical interpretation of the link between the G5 and G6 regions is required.

The complex network facilitates a simple analysis of the relationship between East Asian cities. Unlike previous studies, we incorporate temporal factors in the relationship. Through this, we discover new relationships and characteristics of rainfall in East Asia. During the analysis, two methods (vital node identification and multiresolution community detection) are beneficial for analyzing the network making reliable results. The results verify that our research framework using a complex network is a helpful process for studying relationships in regions. The frame contains not only topological analysis, but also statistical analysis and considers temporal factors. Also, in the end, it reflects climate cycle factors and reveals their characteristics.

5 Conclusions

Concurrent floods in East Asia inundate the firm's production facilities at multiple locations simultaneously, causing supply chain disruptions at the global level. In this study, we analyzed the spatial relationships of rainfall between major cities in East Asia using a complex network. The East Asia rainfall network comprises major cities (nodes) and correlation coefficients (links). Once created the network, vital node identification and clustering analysis were conducted using adjacency information entropy and multi-community detection. Cross-mutual information defined relationships between cluster groups in East Asia. The results revealed that the network reflected the rainfall characteristics of East Asia and the relationships significantly affected vital nodes and clustering analysis. In addition, we observed that Southeast Asia and northwest China have a strong relationship. The study observed that although the computational burdens of implementing complex network analysis is not so high, the method accurately reflects the relationship between regional rainfall and can be used to analyze the relationships between various weather factors. In a subsequent study, we intend to evaluate the applicability of complex network methodology to interpret key climate factors, such as ENSO, IOD, and NAO, which have complex interconnection characteristics.

Code/Data availability

The Asian Precipitation – Highly Resolved Observational Data Integration Toward Evaluation (APHRODITE) grid precipitation dataset is available online at APHRODITE's Water Resources (http://aphrodite.st.hirosaki-u.ac.jp/).

Author contributions

K. Kim, J. Jung and S. Kim designed and conducted the research. K. Kim analyzed the results, with feedback from H. S. Kim,
295 M. Haraguchi, and S. Kim. K. Kim prepared the paper, with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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