Author’s response

We got third review from three reviewers during discussion interval. The reviewers talked about many factors in the paper. We tried to reflect comments on revised manuscript. We believe that the paper is substantially improved as the result of the revision. We wrote point-by-point response (in blue) to reviewer’s comments (in red). Also, we put revised part of the manuscript in black.

<Reviewer 1>

1) (Line 24) ”occurred worldwide during 2000 to 2020“, it should be: “during the period from 2000 to 2020”.

   - ➢ Following the above comment, we changed the Line 24 like below.

     - (Line 24) an annual average of 165 flood disasters occurred worldwide during the period from 2000 to 2020……

2) (Line 65) ”Using the correlation coefficient makes that a network reflect relationship between region“: this pharse should be rewritten in a better way

   - ➢ The current expression about Line 62 is not clear for understanding the meaning. Therefore we changed it like below.

     - (Line 65) By using the correlation coefficients as weights, it makes the network to reflect relationships between regions.

<Reviewer 3>

1. Major revisions

1) The authors rank the importance of the nodes (cities) based on the value of adjacency information entropy and average link weight. They have explained why some locations have a low rank. However, there is no physical interpretations of the cities having very high/low entropy values. Are these cities more prone to flooding due to extreme rainfall from monsoon/typhoons from the South China Sea ? Also do they know any reason why the group of cities in the north of the map have low values compared to those south ? Such an explanation would explain the purpose of conducting the vital node identifictation methodology.

   - In vital node identification analysis, nodes with high ranks have many links with other nodes and their link weights have large value. This study constructed an East Asia rainfall network using similarity of rainfall between 24 major cities. Therefore if a node has high similarity with other nodes, it would contain many links having large weights and place at a high rank in the vital node identification analysis. The nodes in high rank have a common thing that they are located near the major moisture source of East Asia (Hong Kong SAR, Pearl River Delta, Shantou – The South China Sea; Kuala Lumpur and Ho Chi Minh city – The Indian monsoon ; Manila – The East Asian monsoon). We checked the rainfall of the high-rank cities and they have higher rainfall intensity and rainfall days than other cities. On the other hand, low-rank cities are commonly located in the north part of study area have lower rainfall intensity and rainfall days because they are far from the moisture sources. Through the vital node identification, we could check the major moisture sources in East Aisa. We added the results of the vital node identification in parts 4.2 and 4.5. We hope readers understand what we found in the vital node identification analysis.

     - (Line 195-197) We also find another common thing between high-rank cities that they are located in the beginning of impact of the main influence factors in East Asia rainfall. We will describe this in Section 4.5.
     - (Line 271-285) 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 and node at the beginning of two monsoons (Indian and East Asian) were highly ranked, and node's location is one of the essential factors in identifying vital nodes. In the rainfall complex network research, the high rank nodes mean that they are important sites for the propagation of rainfall event. Based on the interpretation of high-rank node, we verified that the South China Sea and two monsoons are the primary moisture sources in East Asia. The South China Sea supplies a huge amount of moisture into East Asia, and the two 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. Kuala Lumpur and Manila are also in high ranks. They have a

common thing their location is at the beginning of each major monsoon influence. The two monsoons pass Kuala Lumpur and Manila first and then move like Figure 7. Because of these characteristics, high-rank nodes have higher rainfall intensity and the number of rainfall days compared to other cities. On the other hand, low-rank cities have low rainfall intensity and the rainfall days. Because the low-rank cities commonly are located in the north which is very far from the moisture sources, the low rank cities get less moisture and have less similarity to other cities. Through vital node identification, we could find the major rainfall influence elements in East Asia and it help to interpret the relationship between groups in Section 4.4.

2) I like how the clustering analysis identify the cities having similar rainfall patterns. However, the authors only explain about Seoul and Kuala Lumpur as to why they are isolated from all groups. There is no interpretation of the cities with form groups. I have a feeling that some groups may be formed because the particular cities likes in the basin of the same river, for instance, G4 is in the Yellow river basin and G3 in the middle/lower reaches of the Yangtze, which maybe the cause of similar rainfall characteristics. Such knowledge is important to predict concurrent floods in multiple locations. Could you please check if such is the case of most clusters ?

- To check the reviewer's comment, we used global basin and river data from HydroSHEDs. Through the data, we found that nodes of some groups are located in the same basin or have the same river. However, not all groups had the above characteristic. The multiresolution community detection is based on link weight. As mentioned in the answer about the first comment, because the network is based on rainfall similarity, we could judge that nodes forming the same group have high rainfall similarities with each other, and also similar rainfall characteristics. The rainfall is caused by a combination of various factors such as weather, topographic and hydrologic elements. Therefore, if two regions have a high similarity, we could interpret that the regions have many same common factors which are affecting rainfall. However, since this study used only rainfall data, we could not confirm which factors make nodes have high rainfall similarity. These factors are very important to finding rainfall relationships and also predict concurrent floods in multiple locations as the reviewer mentioned. Therefore, in the future study, we will focus on this part and find the common factors among the groups.

  - (Line 289-295) We also tried to find common physical factors between nodes in the same group. We found that nodes of some groups are located in the same basin or share the river. However, these factors do not apply to all groups. The cluster analysis result is conducted based on the similarity of rainfall. Rainfall is a meteorological phenomenon caused by a combination of various factors such as geographic, hydrologic, meteorological and ecological elements. If two regions have high similarity in rainfall, they share similar characteristics of factors influencing rainfall. The study tried to find common factors that make groups, but failed to find them. These factors are essential to predict concurrent floods in multiple locations. Therefore, in the future study, we will try to find what factors make the high similarity between nodes in the same group by using geographic, meteorological, and hydrological data.

3) I wonder if lowering the threshold value in the clustering analysis, leads to bigger clusters and unravels grouping together of those clusters which are found to be related in the time lag analysis. For instance, G2, G3, G4 and G6 may be related as they are linked by the anthicyclone and two ore more the groups fall in the same cluster when a lower threshold is chosen. Has the authros verified that ?

- We conducted cluster analysis according to threshod by 2.5% intervals from 95% to 75%. In the cluster analysis result, When thresold became 92.5%, Group 5 and Group 7 were merged. After 85%, Group 3 and Goup 6 became the same group. In 80% and 77.5%, Group 8 was added to Group 5+7 and then Kuala Lumpur add to Group 5+7+8. Rather than what the reviewer expected, we confirmed that the groups in Southwest were firstly being merged. And then there is a merger in the middle part of the study area. In the maximum cross mutual information result, groups at southwest part had a higher value between them compared to groups in the north. This means that southwest groups have a high simlarity of rainfall to each other. Therefore, they become a huge cluster when the threshold is 75%. We added the result of cluster analysis according to the various threshold in part 4.5.

  - (Line 298-302) This result could also be confirmed when creating groups using various thresholds in Section 4.3. When threshold became 92.5%, Group 5 and Group 7 were merged. After 85%, Group 3 and Group6 became same group. In 80% and 77.5%, Group 8 was added to Group 5+7 and then Kuala Lumpur add to Group 5+7+8. As you can see in Figure 6. Group 7 and Group 8 has strong relationship with Group 5 because of the two monsoon and Group 3 and Group 6 also have high relationship because of anomalous anticyclones.
  -

4) Since the authors used the rainfall time series of the whole year for the anlaysis, how do they know while climatologically imerpreting in Sec. 4.4, that the relation between groups is due to Indian monsoon which takes place in summer, or that the anticyclone is not specific to a certain season ?

- In East Asia, 80-90% of rainfall occurs in summer due to monsoon and typhoons in summer. Therefore, most of the characteristics of rainfall are formed by summer phenomena. Because of characteristics of rainfall in East Asia, past studies have also conducted research on summer phenomena to find relationships, features and weather system of rainfall. Accordingly, this study also conducted analyzing rainfall relationships based on summer phenomena. We added the above reason in part 4.4.

  - (Line 239-240) For founding reasons of rainfall relationship in East Asia, it need to analyze East Asian summer rainfall system. Because East Asian summer rainfall contain more 90% of total rainfall in East Asia (Chen et al., 2015). 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 (Chen et al., 2015).

- (References) Chen, F., Xu, Q., Chen, J., Briks, H. J. B., Liu, J., Zhang, S., Jin, S., An, C., Telfod, R. J., Cao, X., Selvaraj, K., Lu, H., Li, Y., Zheng, Z., Wang, H., Zhou, A., Dong, G., Zhang, J., Huang, X., Bloemendal, J., and Rao, Z.: East Asian summer monsoon precipitation variability since the last deglaciation, Scientific Reports, 5, 1186, https://doi.org/10.1038/srep11186, 2015.

2. Minor revisions

1) The main conclusions of the paper is not clear when reading the abstract. The concluding statement should talk more about the authors' findings.

➢ We agree with the comment about the abstract. We expressed the result of the study very briefly. Therefore, this time, we added more detailed results of the study in the abstract. Through the revised abstract, readers will be able to better understand the contents and results of the paper.

- (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 rainfall similarity 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. In the vital node identification analysis result, high-rank nodes are cities that are located near main vapor providers in East Asia. Through the multi-community detection, the groups were clustered to reflect the spatial characteristics of the climate. In addition, the climate links between each group were identified through the cross-mutual information considering the delay time for each group. We found a strong bond between northeast China and the south Indochina Peninsula and verified that the links between each group originated from the summer climate characteristics of East Asia. The result of the study shows that complex network analysis could be a valuable method for analyzing the spatial relationship between climate factors.

2) There is a consistent confusion created by the consistent usage of the term "correlation coefficient" synonymously in place of "similarity measure". Since correlation coefficient is a type of linear simillartiy measure, whereas mutual information is nonlinear, they are different. It is also not clear in the abstract, introduction and methodology Sec. 3.1.

Therefore whether the authors use mutual information or correlation in their work, Kindly correct it.

➢ We understood "Correlation coefficient" as a word containing both linear and non-linear correlations. After checking the comment about the correlation coefficient, we investigated it and found that the real meaning is not the same as what we knew. Therefore, we changed all the terms related to the correlation coefficient in our paper. Belows are some parts of revised content in the paper. Please check the whole revised thing in the paper with track version.

- (Line 66-70) 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 (link) has a similarity as a weight. By using the similarity measures as weights, it makes the network reflect relationships between regions. Using the similarity measure makes a network reflect the relationship between region.
- (Line 121-123) The most widely used methodology is the similarity measure (Donges et al., 2009). Depending on the value of the similarity calculated between two nodes, the researcher can define whether a link exists.
- (Line 129-130) MI can consider the nonlinearity of the data and has the advantage of calculating the similarity between different data sizes (Goyal, 2014).

3) Figure 5 has a typo in labelling of boxes G2 and G3.

➢ We checked Figure 5 and revised the Figure 5 like below.

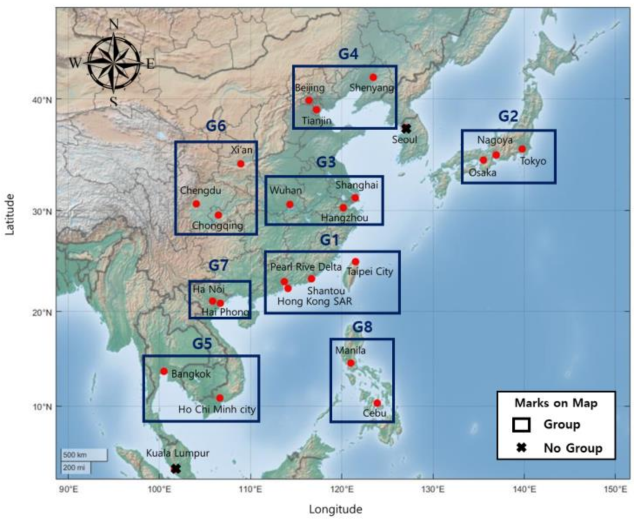

Figure 1. Group of nodes using multiresolution community detection; there are 8 groups in the

East Asia; G1(Pearl River Delta, Hong Kong 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.

4) In the data, it is not clear if you use a single grid point from APRODITE to represent each city of a group of grid points.

   - In this paper, the grids where each city belongs were identified from the APRODITE data which have 0.25x0.25 degree size. And rainfall data was extracted from the grid for constructing rainfall data of 24 major cities in East Asia.

     - (Line 94-95) We extracted the rainfall data from the grid($0.25^{\circ} \times 0.25^{\circ}$) where each city belongs.

5) Line 58-59 in the introduction is incorrect. A complex network may be of several types. What the authors seems to refer to are functional climate networks in which connectivity is defined on the basis of "statistical interdependence" between the pairs of nodes. Please change the sentence.

   - In the cause of complex networks in hydrology and meteorology fields, most of them used the statistical interdependence method. We generalized and expressed the above sentence in Line 58-59. However, there are various link definition methods for making complex network according to the subject. Therefore, the sentence was modified by making the expression more clearly as a complex network in the hydrology and meteorology fields.

     - (Line 61-62) The complex networks in hydrology and meteorology fields defined connectivity using statistical interdependence methods.

6) Line 106 in Sec 3.1, a node need not be a fixed element. A node in a complex network is a dynamical unit, it may be fixed, movable, disappearing. In case of climate network, the nodes are spatial grid points which represent a dynamical subsystem. Kindely correct the sentence.

   - Line 106 is also thought to be the same problem with comments 5 in minior revisions. We revised Line 106 as the most common definition of a node. Also, we add a reference to the paper which contains the definition of a node.

     - (Line 111-112) A node represents some entity or agent that serves as a point of intersection/junction within a network (Kivelä et al., 2014).

- (Reference) Kivelä, M., Arenas, A., Barthelemy, M., Gleeson, J. P., Moreno, Y., and Porter, M. A.: Multilayer networks, Journal of Complex Networks, 2(3), 203-271, https://doi.org/10.1093/comnet/cnu016, 2014.

7) Sec. 3.2 in methodology, please add a sentence on the relevance of vital nodes or high degree nodes in climate system.

  ➢ We wrote down the meaning of important nodes in rainfall complex networks by refering to related studies. Vital nodes in the rainfall complex network are important points for the propagation of rainfall event.

    - (Line 146) In the rainfall studies, vital nodes are interpreted as important points for propagation of rainfall event.

8) Sentence "Each node has different link weights" on line 169 is confusing, as link weight is between pairs of nodes. Please clarify or remove.

  ➢ Line 169 makes readers confusing. So, we deleted Line 169.

9) In line 175, authors talk about narrower or wider range of average, maximum and minimum link weights. They can use standard deviation of the range of av., max., min. Link weights instead of quantify the "range".

  ➢ We agree that it is better to express range as standard deviation. We calculated the standard deviation of average, minimum and maximum vales and then compared them.

    - (Line 181-182) 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 standard deviation of average, minimum and maximum values are 0.041, 0.033 and 0.394. The standard deviation of maximum values had 10 times larger value than the minimum values.

10) Section 4.2, please specify that high ranking nodes means node of high adjacency.

  ➢ To make the readers know about the result meaning, we clarified the Line 183-184 like below.

    - (Line 190) The cities with high ranking nodes are located around the South China Sea (Fig. 4). In addition, they have a high adjacency in the adjacency matrix.

11) I do not understand in lines 186-187. 'High ranking nodes in center of the maps.... low-ranking nodes are diametrically opposed.... ' Kuala, a high ranked node is not in

center. ′diametrically opposite′ is not clear. Please remove the explanation if it is not needed.

- ➢ Line 186-187 had been added in the Second revision because another reviewer asked for it. But we agree that it is not clear to readers. We eliminated the Line 186-187.

12) Line 184-185 ′low mean of MI′ and ′large average of MI′, do you refer to the second column of average link weight in Table 2 ? Please clarity.

- ➢ Both are meaning of the average value of mutual information in Table 2. We changed 184-185 for clarifying the meaning.

  - (Line 190-191) Cities with low-rank nodes are in the northeast outskirts, except for Taipei, and have a low value of average MI.

13) Line 233 onwards, Indian monsoon does not move northwest, rather the moisture bearing cross equatorial south-westerly low level jest coming from the Somalian coast, which causes Indian monsoon, moves northwest.

- ➢ One of the important thing generating rainfall events is supply and moving of moisture. We interpreted that moisture from the Indian monsoon is moving to the northwest direction by the monsoon. However, after receiving the above comment, we searched about the related information and checked many related papers. We finally conclude that low-level jest move moisture to East Asia region. Therefore, we revised all related sentences after Line 233.

  - (Line 246-249) Water vapor from 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 movement of water vapor from Indian monsoon is caused by low level jet stream from the Somalian coast.

14) Replace ′vapour provider′ and ′vapour′ in line 258 with ′moisture source′ and ′water vapour′ respectively.

- ➢ We revised "Vapour provider" as "moisture source".

  - (Line 274-275) Based on the interpretation of high-rank node, we verified that the South China Sea and two monsoons are the primary moisture sources in East Asia.

15) Mention ’belonging coefficient’ specifically in line 261.

- ➢ We revied “The coefficient” as “the belonging coefficent”.

  - (Line 286) As described in Section 4.3, the belonging coefficient of each node was calculated by using the link weight.

<Reviewer 4>

1) Why not directly use the original precipitation points (or maybe a slight coarsen resolution, if the orginal resolution is too small), because i see from Fig. 2 that in East Asian region, there are a lot of points more than 24 ? 24-city is a quite small-scale. That means the constructed networks has only 24 nodes. Even for the selected 24 cities, there are probably several stations insdie each of them. Then it would be better to consider the original dataset, because the aggregation of rainfall data for each city is essentially omitting some local information. Besides, as far as i know, the computational complexity (that is, the actual running time) for a network with fro example 1000 nodes, can still be pretty small. Another reason to consider a higher resolution is that is delivers a more convincing conclusion ?

   - This study is one of the following studies about "Correlated Risk for Heavy Precipitation in Mega-cities in East Asia" in references. In "Correlated Risk for Heavy Precipitation in Mega-cities in East Asia" study, we analyzed the relationship between several weather-ocean events (El Nino and Southern Oscillation, West Pacific pattern, Idian Ocean Dipole etcs) and rainfall of major cities in East Asia. In the current study, we focused on the relationship between the major cities and evaluation of complex network analysis methods in weather system research. Through all related studies, we intend to finally analyze the rainfall of the entire East Asia region by applying a complex network methodology.
     We would like to apply the complex network method to a small scale network first. Because we could easily understand and interpret the subject before applying to a huge scale network. Therefore, we only treated the major cities of East Asia in this study. In the future study, we will make a rainfall network of East Asia consisting of more than 1,000 nodes and analyze the network with various analysis method. Regarding rainfall data, we needed grid data for conducting the final research. In the beginning of the study, we evaluated several grid data and selected the APHRODITE data which provides high-resolution rainfall data about East Asia. However, since the APHRODITE data has several problems which the reviewer mentioned in the comment, we will compare the APHRODITE data with observed data for checking missing data in the future study.

2) Why use vital node identification and community detection together ? And how they both contribute to the final conclusion ? In the domain of complex network analysis, vital node identification and community detection are different research probelms, although there might be some overlapping between then. I initially thought there might be some connections between the results obtained from teses two methods in this manuscript. But it seems to me that they are separate contents. In my opinion, vital nodes are possbily useful for disaster mitigation, while community detection could be useful for finding out regions of similar climatological behavior, but there might be a lack of explanation on why they should be considered together, and specifically, how they help in obtaining the final conclusion.

- The study used vital node identification and multiresolution community detection method. Vital node identification method identifies important nodes in a network. In the rainfall network, high-rank nodes mean important places for the propagation of rainfall. In the vital node identification result, nodes in high rank have a common thing that they are located near the major moisture source of East Asia (Hong Kong SAR, Pearl River Delta, Shantou – The South China Sea; Kuala Lumpur and Ho Chi Minh city – The Indian monsoon ; Manila – The East Asian monsoon). We checked the rainfall of the high-rank cities, and they have higher rainfall intensity and rainfall days than other cities. On the other hand, low-rank cities are commonly located in the north part of the study area have lower rainfall intensity and rainfall days because they are far from the moisture sources. Multiresolution community detection method can cluster nodes with similar characteristic in a network according to the threshold. In the study, cities with similar rainfall characteristics were clustered through community detection, and the network could be simplified through clustering. The two methodologies had different results, but the conclusions have helped interpret rainfall relationship between major cities in East Asia. Through the vital node identification, we could check the major moisture sources in East Asia and help to interpret the relationship between groups. We added what we got from both methods and how they helped to interpret the rainfall system in part 4.5.

  - (Line 310-317) During the analysis, vital node identification helped to identify important sites for propagation of rainfall and major moisture sources in East Asia. The vital node identification is a useful method to analysis the system or phenomena. Therefore, it can be used for researching natural disaster or meteorological system. Multiresolution community detection method found cities having similar rainfall characteristics according to threshold. It made the groups having similar characteristics and simplified the rainfall network. This helped to understand rainfall relationship between the East Asia major cities. Two methods draw out different results but, they help to interpret the results. For example, the major moisture sources found by vital identification helped to explain the relationship between groups. In addition, their results ultimately helped to understand the rainfall system in East Asia.

3) Regarding the community detection, how is the quality of community structure (or groups in this manuscript) measured? Also, how is the threshold "t" determined? When applying community detection, commonly accpeted measures include modularity and normalized mutual information. But there is a lack of explanation in this regard. The threshold "t" could be any value between the range of [0,1]. Different values could lead to different forms of groups. If there is not a standard way to determine what it would be, then why the group in Fig. 5 would be chosen as the final result.

- The study evaluated the results of clustering with Newman-Girvan modularity. We set a threshold group divided by 2.5% interval from 95% to 75% and applied the group to the network. We calculated Newman-Girvan modularity about all cluster results and found that 95% threshold had the highest value in modularity. In Newman-Girvan modularity, a clustering result can get high scores if they are densely connected internally, but only weakly connected to other group. Based on the above result, we concluded that the 95% threshold is the best parameter for clustering analysis.

For selecting threshold problem, there is no clear method. The developer of the multiresolution community detection method also pointed out the threshold selecting problem in their paper. However, they showed that the larger the threshold, the more clusters and more details can be heard. Therefore, the study performed cluster analysis by applying a high threshold. We added the cluster evaluation methodology and its result in parts 3.3 and 4.3 each.

- (Line 166-171) For evaluating the result of the cluster method, we used Newman-Girvan modularity. The Newman-Girvan modularity method compares the number of links connecting nodes inside a group of nodes with an expectation of this number under a random null model (Newman & Girvan, 2004). The modularity (Q) is calculated by Eq. (9). Where, P is a cluster of node groups (P = $\{g_1, g_2, \cdots, g_a\}$), and g_a is a node group. m is a total weight of links. The modularity measure assigns high scores to communities if they are densely connected internally, but only weakly connected to other group. We set threshold groups divided by 2.5% intervals from 95% to 75% and calculated the Newman-Girvan modularity according to the threshold groups.

$$Q = \frac{1}{2m} \sum_{P \in g_a} \sum_{i,j \in g_a} (A_{ij} - \frac{k_i k_j}{2m}) \quad - \quad (9)$$

- (Line 216-218) For evaluating the cluster result, we calculated the Newman-Grivan modularity. We set the divided by 2.5% intervals from 95% to 75%. In the modularity result, 95% show the largest modularity (Table 3). In the Table 3, there are thresholds having same value of modularity. Those thresholds have same result of clustering.

Table 1. Result of Newman-Grivan modularity according to threshold

Threshold	95%	92.5%	90%	87.5%	85%	82.5%	80%	77.5%	75%
Modularity	0.0313	0.0311	0.0311	0.0311	0.0309	0.0309	0.0294	0.0286	0.0286

4) From the current version of the Abstract, the main conclusion is not emphasized

➢ We agree with the comment about the abstract. We expressed the result of the study very briefly. Therefore, this time, we added more detailed result of the study in the abstract. Through the revised abstract, readers will be able to better understand the contents and results of the paper.

- (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 rainfall similarity 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. In the vital node identification analysis result, high-rank nodes are cities located near main vapor providers in East Asia. Through the multi-community detection, the groups were clustered to reflect the spatial characteristics of the climate. In addition, the climate links between each group were identified through the cross-mutual information considering the delay time for each group. We found a strong bond between northeast China and the south Indochina Peninsula and verified that the links between each group originated from the summer climate characteristics of East Asia. The result of the study show that complex network analysis could be a valuable method for analyzing the spatial relationship between climate factors.

5) Contents between 153 and 165 (both equations and paragraphs) should be reorganized in a more fomral way.

- We checked HESS instruction and recently published papers in HESS journal and then edited not only Lines 153-165 but also Lines 135-144.

  - (Line 140-146) The first step is calculating strength of each node in a weighted network (Eq. (2)).

$$k_i = \sum_{j \in \Gamma_i} w_{ji} \quad - \quad (2)$$

where, 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. Next, estimate an adjacency degree of each node (Eq. (3)).

$$A_i = \sum_{j \in \Gamma_i} k_j \quad - \quad (3)$$

A_i is an adjacency degree which means total weight of neighbor nodes of node i. Based on Eq. (2) and Eq. (3), selection probability can be calculated (Eq. (4)). Eventually an adjacency information entropy of a node is calculated based on Eq. (5).

$$P_{i_j} = k_i / A_j \quad - \quad (4)$$

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

After comparing the calculated adjacency information entropy of each node, the importance is determined according to the descending power. In the rainfall studies, vital nodes are interpreted as important points for propagation of rainfall event.

- (Line 154-166) This method has the advantages of forming groups more accurately and faster than other methods. For making groups, belonging coefficient of the nodes should be calculated. First step for estimating belonging coefficient is defining 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. After defining distinct paths, it need to calculated link intensity of each link. The equation of link intensity is same as Eq. (6).

$$I_P(e_{ij}) = \begin{cases} \sum_{p=1}^{P} \alpha_p \times \dfrac{\sigma(path_p(v_i, v_j))}{\min(w_i, w_j)}, & e_{ij} \in E \\ 0, & otherwise \end{cases} \quad - \quad (6)$$

Where, $\sigma(path_p(v_i, v_j))$ 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. Based on link intensity, find links which have larger value of link intensity than a threshold and create a group of nodes with the identified links (Eq. (7)).

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

Where, t $(0 < t \leq 1)$ is the selected threshold, and c_u is a group of nodes. The threshold is determined according to researcher personal view. Final step is calculating belonging coefficient (I_P) of the nodes in node set u (c_u) (Eq. (8)).

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

6) Fig. 5 has a label probel, two "G2".

➢ We checked Figure 5 and revised the Figure 5 like below.

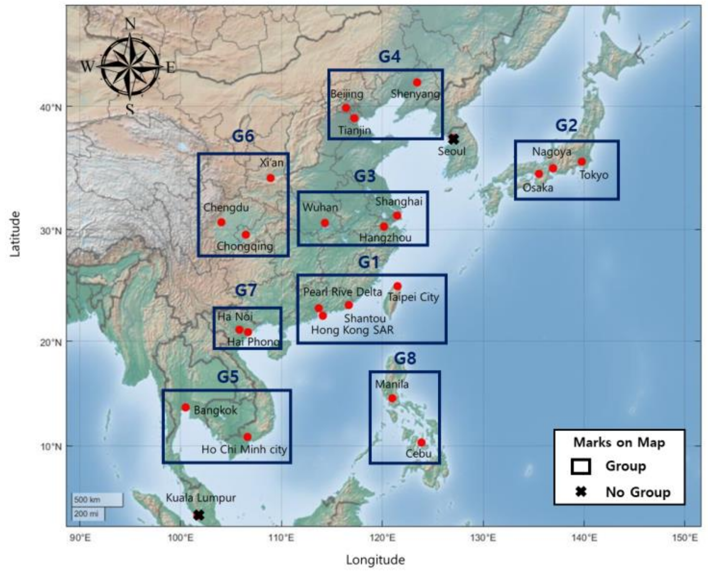

Figure 2. Group of nodes using multiresolution community detection; there are 8 groups in the East Asia; G1(Pearl River Delta, Hong Kong SAR, Shantou, Taipei City), G2(Osaka, Nagoya, Tokyo), G3(Wuhan, Hangzhou, Shanghai), G4(Tianjin, Shenyang, Beijing), G5(Bangkok, Ho Ch i Minh City), G6(Xi'an, Chengdu, Chongqing), G7(Hanoi, Haiphong), G8(Manila, Cebu); Seoul and Kuala Lumpur did not make group with other nodes.