Response to Referee #1

We thank the referee for constructive comments and comprehensive analyses of our manuscript. We have fully addressed the comments. For your convenience, we now provide our point-by-point responses to all the concerns as detailed below. Note that the referee's comments are in italic font (blue), whereas our reply is not italicized and some corrections (red) in the revised manuscript are attached. All figures are placed at the end of text.

General: The general idea of the paper seems relevant and interesting to me. Complex networks are a reasonable choice to study teleconnections in climate systems. Their use in climate science has increased in the last decade, but I am not aware of an application to this region. Furthermore, two-parameter networks are still a rather novel method in this field. However, there have already been several studies linking SST and rainfall in China using different approaches (Zhou et al. 2010, Wu et al. 2012). Furthermore, the chosen region is rather small and its special importance (if there is any) was not made clear to me. I do not see a reason speaking against extending the study area to China as a whole.

Response: We appreciate that our paper is interesting to the referee. Rainfall in this region is the first time to be studied by using the network approach. Although there have been many studies of the linkages between the SST and rainfall in China, we believe that their approaches are different with ours. Complex networks allow us to detect more physical information. Based on the referee's comments, we renamed the chosen area as Northwestern South Asia (NWSA), since the chosen area is little larger than Southwest China. We chose the area as our study region, because in the summer of 2006 and 2011, NWSA suffered from record-breaking drought events leading to an economic loss of 3 billion dollars, 16 million people cannot easily access to drinking water, more than 50 million people were affected by this disaster and nearly a million hectares could not producing crops(Shi et al., 2015). Droughts and floods have close relation with the rainfall in NWSA, so the investigation of rainfall in this region has been an important topic deserving high attention from the meteorologists. The mechanism of precipitation in NWSA is quite complicated, since the East Asian monsoon, Indian monsoon both potentially influence the rainfall in this region. We improved our text in the revised manuscript.

Corrections:

(Line 1-3) Abstract. Droughts and floods have frequently occurred in Northwestern South Asia (NWSA) in this century. The mechanism of precipitation in NWSA is quite complicated, since the East Asian monsoon, Indian monsoon and et al. potentially influence the rainfall in this region. Prediction of precipitation in NWSA has become a difficult and critical topic in climatology study.

(Line 12-19) In recent decades, natural hazards (such as droughts and floods) have occurred frequently in Northwestern South Asia (NWSA) due to climate change, causing a large number of casualties and property losses (Ha et al., 2019; Gao et al., 2017; Wei et al., 2018). In the summer of 2006 and 2011, NWSA suffered from record-breaking droughts events (Zhang et al., 2017). On the other hand, the portion of annual precipitation contributed by extremely heavy precipitation has been found an increasing trend from 1961–2010 in NWSA (Ma et al., 2013). Due to an increasing population and the high risk of natural hazards, NWSA has attracted lots of attention in meteorological research fields. According to CMIP5 multi-model projections, they found that severe and extreme droughts in NWSA increase dramatically in the future, and extremely wet events will also increase (Wang et al., 2014).

C1

The authors mention both floods and droughts as hazards that could be better understood based on this work. However, they do not mention droughts after the introduction. Their inclusion into the abstract is therefore misleading. They are also not showing if the correlations they find actually influence the extreme rainfalls that produce floods or whether the effect is only present for low magnitude precipitation. I am therefore not certain, whether this paper (in its current state) fits the scope of a natural hazard journal.

Response: We thank the referee very much for this valuable comment. Extremely high precipitation is closely associated with a flood event in NWSA. Besides, continuous normal may also cause large value precipitation, which has an important impact on the possible flood events. Meanwhile, the drought event in NWSA always caused by the little precipitation in a long duration. Therefore, if we can properly predict the rainfall in a long ahead of time, which will be of great help for us to deal with the relevant drought and flood events. This study mainly focusses on the possible correlations between rainfall in NWSA and global key regions' sea surface temperature (SST) anomalies through the complex network approach, which may also help us to better predict floods and droughts in NWSA. In order to find out the influence of extreme rainfall on the correlation between rainfall and SST, we replaced top and bottom 5% extreme precipitation in the middle random magnitude precipitation in each grid data series. Then we analyzed the data by using our method and compared the results with those before replacing. Fig. 2 and Fig. 3 show that most of the correlation patterns disappear in Fig. 2 (b), (d), (f) and (h) after replacing the extreme rainfall event, indicating that top and bottom 5% extreme precipitation plays important roles to produce the correlation patterns. Therefore, this study revealed the correlation between the PA and SSTA is quite important for the extreme rainfall analyses, which further show the tightly connection with the drought and flood in NWSA. Therefore, content of this study quite fits the scope of a natural hazard journal.

Corrections:

(Line 126-130) To further prove that extreme rainfall is significantly influenced by these important regions, top and bottom 5% extreme PA is replaced by the random middle magnitude PA in data. Then we employ the same analysis of the new time series. Fig. 2(b), (d), (f) and (h) shows the results after replacing. Comparing with Fig. 2(a) before replacing, some important nodes disappear in Fig. 2(b) after replacing. Similar results also can be found for other seasons. It implies that top and bottom 5% extreme precipitation plays important roles to contribute to the teleconnection patterns.

The used data might not be fit to answer all of the questions the authors pose. They mention the complex topography of the study area, but it is unlikely that a 2.5×2.5^o grid is sufficient to fully represent this complexity. The MSWEP precipitation dataset (Beck et al. 2016) with a resolution of up to 0.1^o and the same temporal range could be better suited for this task. The data is not always described to the necessary extent. It is unclear whether rainfall or rainfall anomalies are studied.

Response: We thank the referee for the comment. Although the horizontal resolution of the NWSA rainfall data is $2.5^o\times2.5^o$, we focused on studying teleconnection between NWSA precipitation anomalies and the global SSTA, reveal the key SST region influence the rainfall in NWSA, the resolution of for rainfall seems not quite crucial, because the SSTA often has impact on large circulation system, for example the SST's impact often covers the entire NWSA region. We think that the main results with high resolution rainfall data will be same as the present study. In our study, precipitation was detrended to get the precipitation anomalies (PA). The analyses in this study are calculated based on the PA and SSTA, relevant descriptions were introduced in the section 2.2. We claimed it in the revised manuscript.

Corrections:

(Line 60-64) First, we remove the seasonal cycle to obtain the time series of the SSTA as (Fan et al., 2017; Meng et al., 2017),

$$Y^{y}(t) = \frac{\tilde{Y}^{y}(t) - \mathrm{mean}\left(\tilde{Y}(t)\right)}{\mathrm{std}\left(\tilde{Y}(t)\right)}, \qquad (1)$$

where $\tilde{Y}^{y}(t)$ is the time series of the daily SST; y stands year and t stands date within a year. "mean" and "std" denote the mean and standard deviation of the SST for all the years on a date t. We use the same way to obtain precipitation anomalies (PA).

The methods are not fully described in at least two cases. First, the removal of the seasonal cycle is mentioned, but not explained in details. Second, the splitting of the time series into seasons is not completely clear. Does this lead to on time series for each season? How do these look like: 3 months data – 9 months gap – months data - . . ., or a gapless series of the 3 months.

Response: Thanks. We explained the details of the removal of the seasonal cycle in the above response. We also improved the explanation about the splitting of the time series into seasons as following corrections.

Corrections:

(Line 68-72) We take 3 months for a season in each year, for example June, July and August are selected for summer. Thus for each grid i in NWSA, we can obtain 117 months daily data for 39 years as the PA time series for a season, $X_i(t)$, where t spans those selected days with 9 months gap for each year. Then the corresponding time series of SSTA can be obtained for as $Y_j(t+\tau)$, where τ is a time delay. Note that the corresponding time series of SSTA depends on the time delay and could be not in the same season as the time series of the PA.

Pearson Correlation is possibly not fit for the data. When explained, the methods are presented in a way that is understandable to a scientific audience. The potential of the complex networks is not fully exploited. Additional network parameters (e.g. betweenness, clustering) could provide further insights and could support the interpretations that the authors make.

Response: We thank the referee for this kind comments. We are considered the additional parameters for our study. We detected and found some significant clusters in our networks. This result was discussed in Section 3.3 of the revised manuscript. We selected the nodes in NWSA with the largest weighted in-degree for each season as showed in Figs. 4 and 5. The largest cluster C_1 on the sea for a node of NWSA is defined by the largest successive area where all the inside SSTA nodes are connected to that node in NWSA. We can obtain the second largest cluster C_2 in a similar way. The large cluster regions can be of help to choose the key region having a crucial impact on rainfall in NWSA.

Corrections:

(Line 149-153) We first select the nodes in NWSA with the largest weighted in-degree for each season as showed in Figs. 4 and 5. The largest cluster C_1 is identified by the largest successive area where all the inside SSTA nodes are connected to that important node in NWSA (Kawale, 2013; Lu et al., 2016). We can obtain the second largest cluster C_2 in a similar way. Figs. 6(a) shows the cluster C_1 (blue) and C_2 (green) which are connected to the nodes of I_{11} (as shown in Fig. 4(a)) for DJF.

The English language of the manuscript is often poor. There are several (> 50) cases of missing words, typos, grammatical mistakes and poor wording. In some cases, this leads to poor understandability. In contrast, the mathematical formulae are well written and described.

Response: We thank the referee for the careful comment. We did our best to improve the text of the revised manuscript.

C2

The title of the paper is misleading to some extent, as most of the grid cells that have a substantial degree lie fully or partly outside of China.

Response: Thanks. In order to avoid misleading, we revised Southwest China as Northwestern South Asia (NWSA) in this study. For clarity, we claimed this in the revised manuscript.

Corrections:

(line 54-55) This area mainly includes Southwest China and its surrounding areas.

The contents of the figures are well chosen. They do however need visual improvement to maximize information gain and understandability. Especially the color maps need improvements. Most figures could be larger in size, as they are hard to interpret in the current form.

Response: We thank the referee for this comment. We have improved these figures in the revised manuscript.

The introduction seems too long and repetitive at times. The discussion of the results could be more thorough. Apart from that, the overall length of the paper seems fitting.

Response: Thank the referee very much. We have rewrote the introduction and discussion in the revised manuscript.

Specific:

I have the suspicion that parts of the presented correlation could be caused by common seasonality in the compared parameters. This is supported by the fact that some of the time lag-correlation plots show a minimum and a maximum that are offset by -180 days (Fig. 6b and 8d). The relationship mentioned in lines 118-119 hints at this as well. Due to this I would appreciate a larger maximum time lag (±365 days) as well as example plots and statistics for rainfall and SSTA.

Response: We thank the referee for the helpful comment. To verify the referee's suspicion, we apply a new shuffling testing. We randomly shuffled the order of years, keeping the variations within each year and then calculate the cross-correlation between the shuffled time series. In Fig. 1, we showed the PDF of correlations for the shuffle data comparing with real data. In this shuffling process, the distribution of values and the autocorrelations and common seasonality in each year has been kept in each shuffled record, while the physical dependencies between nodes tend to be destroyed. If the correlations are significantly higher than the significant threshold, we regard it as a true link; otherwise, it is suspected to be a spurious link. We obtained the threshold $\Delta = 0.1$ by using the 95% confidence significance test combined with a multiple testing correction (Benjamini-Hochberg) as you suggested. Thus the presented correlation cannot be caused by common seasonality in the revised manuscript. We also extended the range of time-lag (±365 days) and obtained the sharp minimums and maximums in Fig. 6-9 of the revised manuscript.

Corrections:

(Line 99-103) In order to verify the significance of the correlation, we compare the PDFs between the real data (red) and shuffled data (blue) in Fig. 1. We randomly shuffle the order of years for each node, keeping the variations within each year to get shuffle data (Fan et al., 2017). Then we calculate the cross-correlation for shuffled data as same as real data. In this shuffling process, the autocorrelations and common seasonality in each year have been kept in each shuffled time series, while the physical dependencies between the SSTA and PA nodes are destroyed.

Instead of using shuffling for the definition of the threshold, I would suggest a classic 95th percentile significance test combined with a multiple testing correction (e.g. Benjamini-Hochberg). Furthermore, Spearman Rank Correlation is a more fitting measure, as the data is likely non-linear.

Response: We thank the referee's helpful comment. We implemented new shuffling testing and 95th percentile significance test combined with a multiple testing as above response. For Spearman rank correlation, we need to order the time series of SSTA for each time-lag to calculate correlation which will spend more time to calculate. Based on the reviewer's good suggestion, we will do this in further studies.

Uncertainty bounds should be stated with each of the derived time lags, as these are likely up to ±40 days in some cases (e.g. Fig. 7d).

Response: Thank the referee. We extended the range of time-lag and uncertainties bounds in Fig. 6-9 have been stated.

Technical:

I will not spellcheck the whole manuscript. A very frequent mistake is the lack of "the" in front of words that require it (e.g. lines 6, 23, 25) or its unnecessary presence in other cases (e.g. lines 16, 28). Verb tenses (e.g. lines 4, 19) and prepositions are two other major problems. I advise the authors to make use of professional spell-checking.

Response: We thank the referee for the comment. We modified these errors and did our best to spell-checking in the revised manuscript.

C3

The color bars of Fig. 2 and 3 should scale linearly. A higher contrast between the different colors would enhance interpretability. Fig. 4 and 5 could need an overview map, of where in the world this is.

Response: We thank the referee very much. We changed the color bars of Fig. 2 and 3 to the scale linearly and higher contrast. We marked the location of NWSA as a purple rectangle in the world in Fig. 2 and Fig. 3. Also we mentioned it in the caption of Fig. 4.

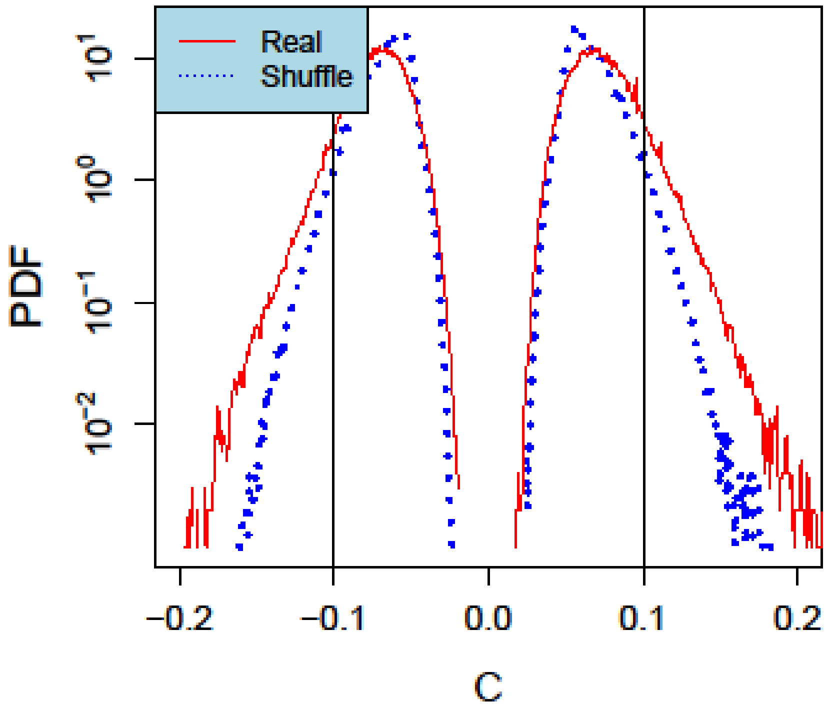

Figure 1. (Color online) PDFs of correlations C_{ij} for real data and shuffle data. Black vertical lines represent the location of the threshold $|\Delta| = 0.1$.

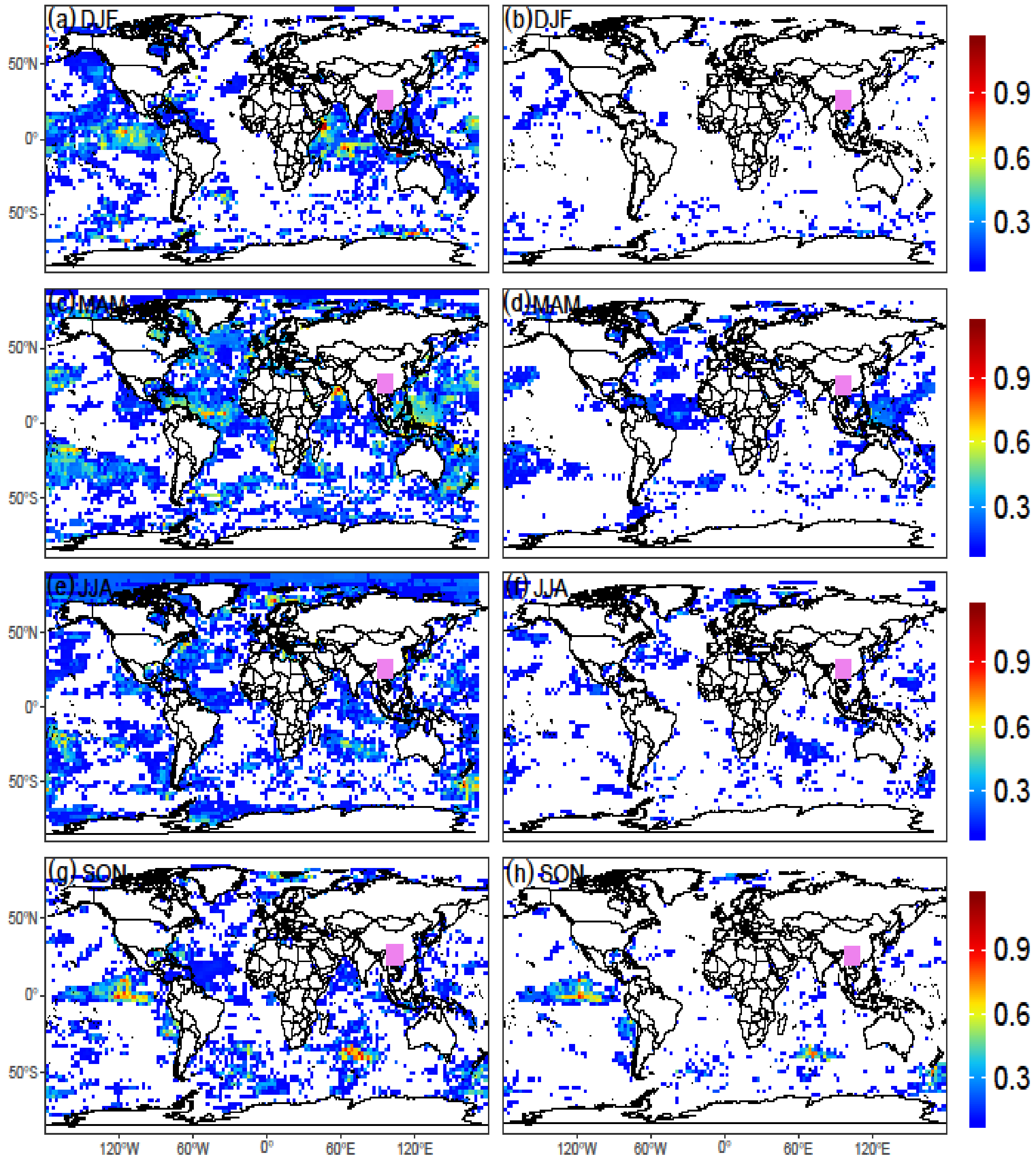

Figure 2. (Color online) Distributions of the positive weighted out-degree for (a) DJF, (c) MAM, (e) JJA and (h) SON. (b), (d), (f) and (h) Same as (a), (c), (e) and (h) but for replacing top and bottom 5% extreme precipitation with middle magnitude precipitation in data. White areas represent zero in maps. Purple rectangle area covers the region of NWSA.

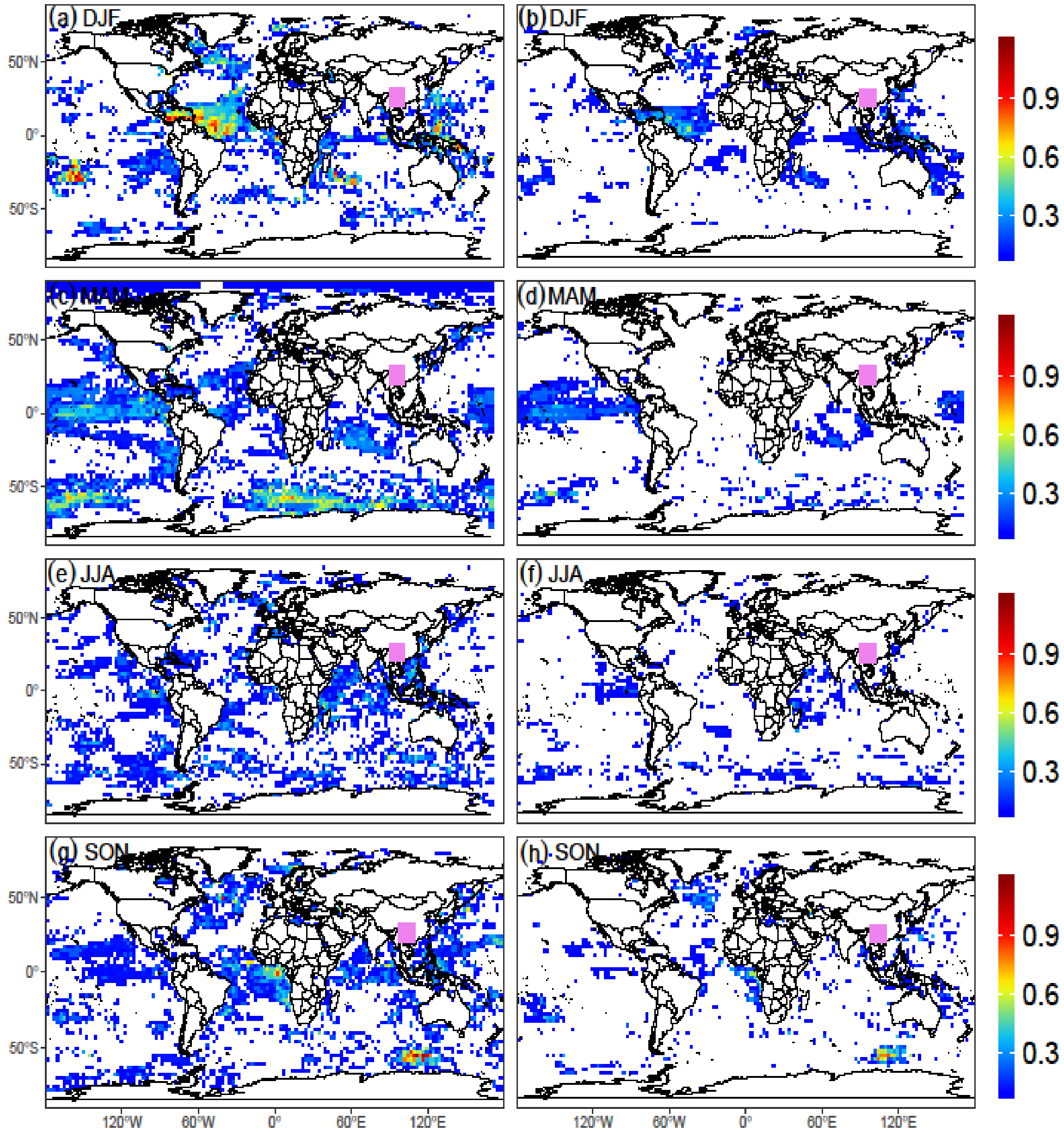

Figure 3. Same as Fig. 2 but for the negative weighted out-degree.

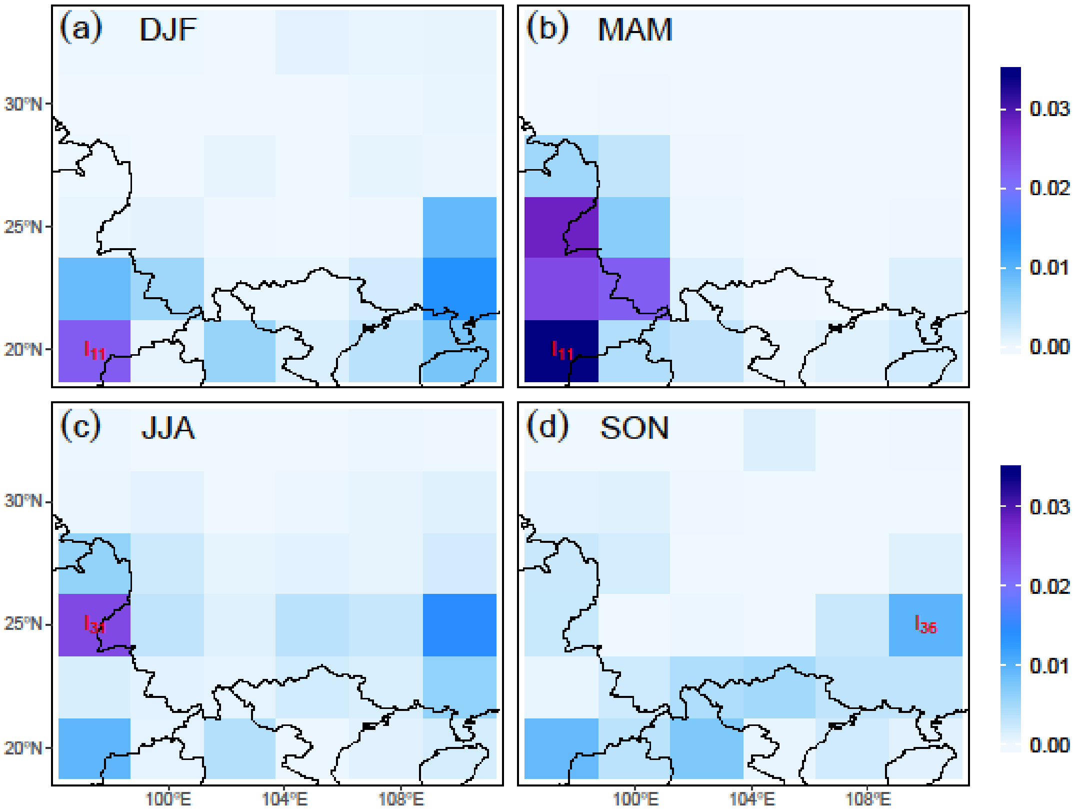

Figure 4. (Color online) Distributions of the positive weighted in-degrees for (a) DJF, (b) MAM, (c) JJA and (d) SON in NWSA. The location of NWSA in the world is shown as the purple rectangle area in Fig. 2. I_{11}, I_{31} and I_{36} are the important nodes in NWSA with the largest positive weighted in-degree in a season.

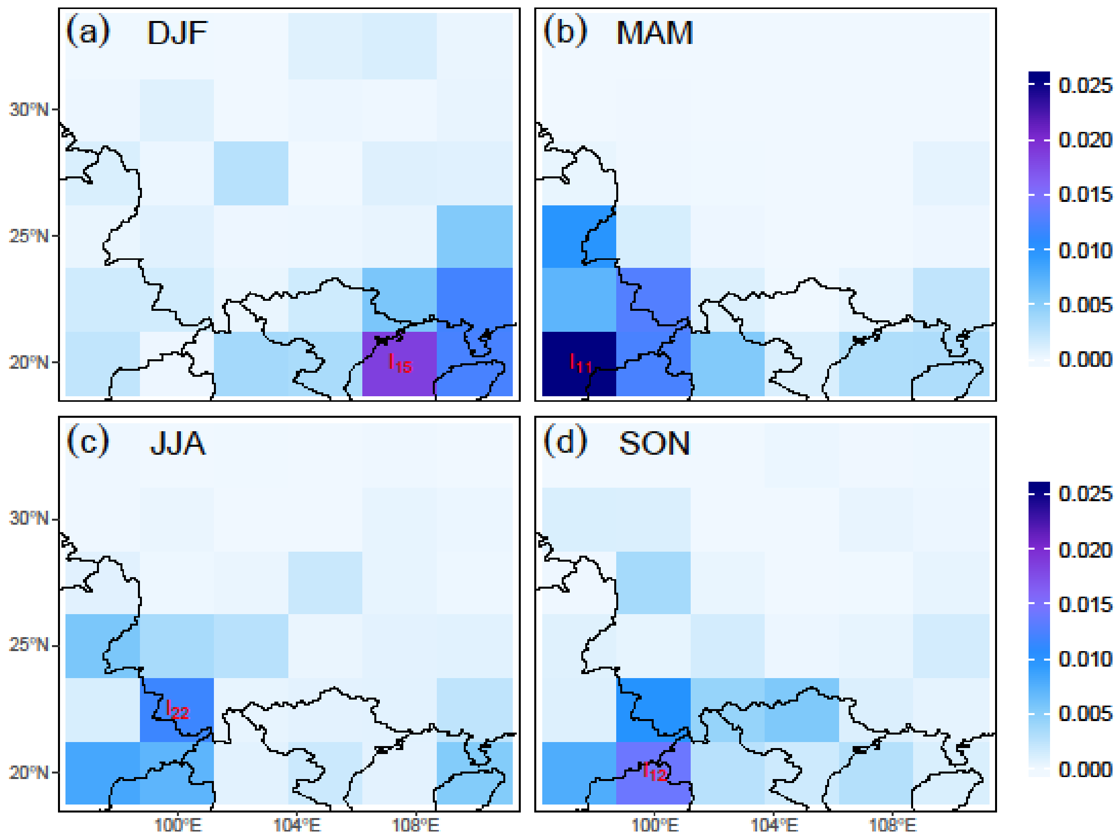

Figure 5. (Color online) Same as FIG. 4 but for the negative weighted out-degree. I_{15}, I_{11}, I_{22} and I_{12} are the important nodes in NWSA with the largest negative weighted in-degree in a season.

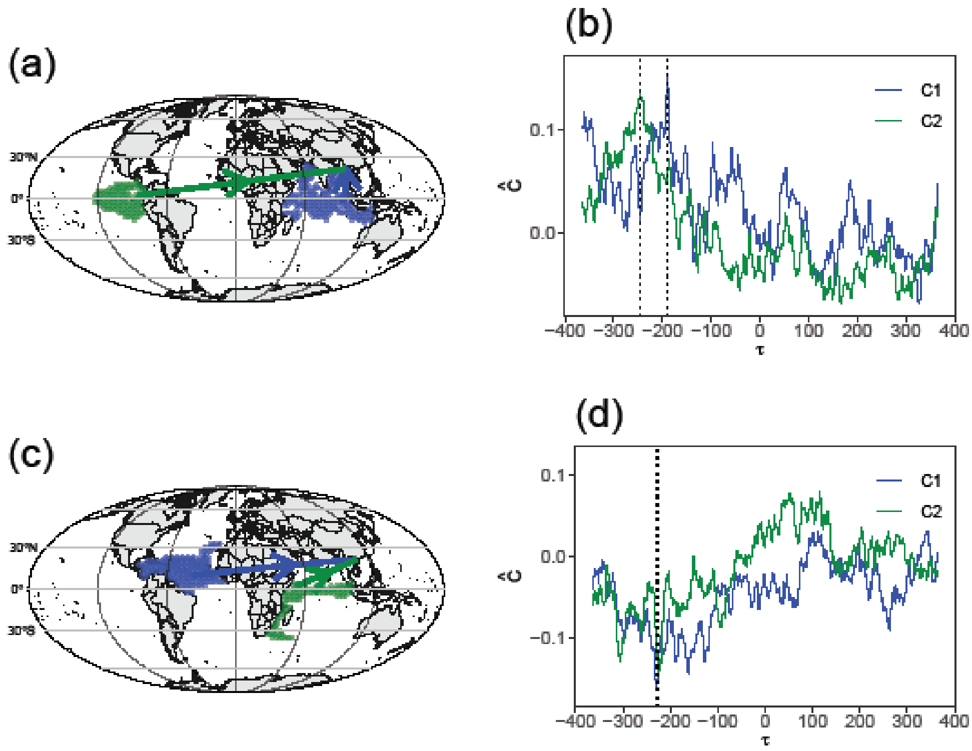

Figure 6. (Color online) Locations of the largest cluster C_1 (blue) and the second largest cluster C_2 (green) that are (a) positively ((c) negatively) correlated with the node .I_{11}, (I_{15}) in NWSA for DJF. The blue and green arrows represent the strongest links from C_1 and C_2 to that node in NWSA respectively. (b), (d) The correlation $\hat{C}$ as a function of the time lag τ corresponding to the strongest links in map (left) respectively. Dashed black line shows the absolute maximum of the correlation $\hat{C}$.

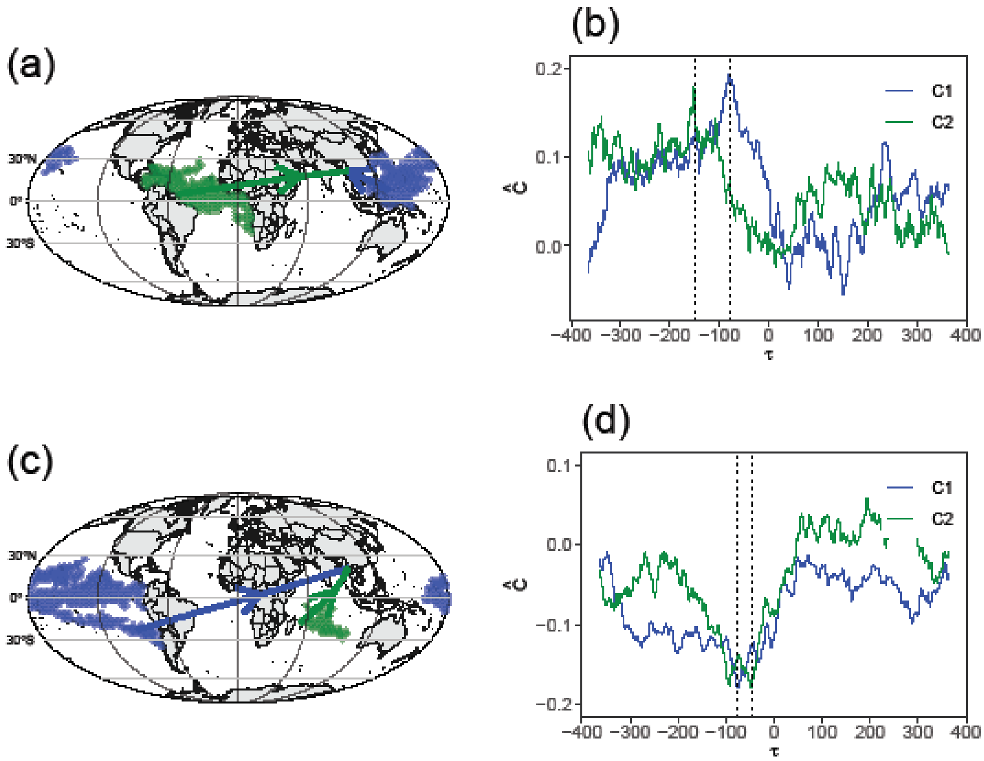

Figure 7. (Color online) Locations of the largest cluster C_1 (blue) and the second largest cluster C_2 (green) that are (a) positively ((c) negatively) correlated with the node I_{11} (I_{11}) in NWSA for MAM. Everything else is the same as Fig. 6.

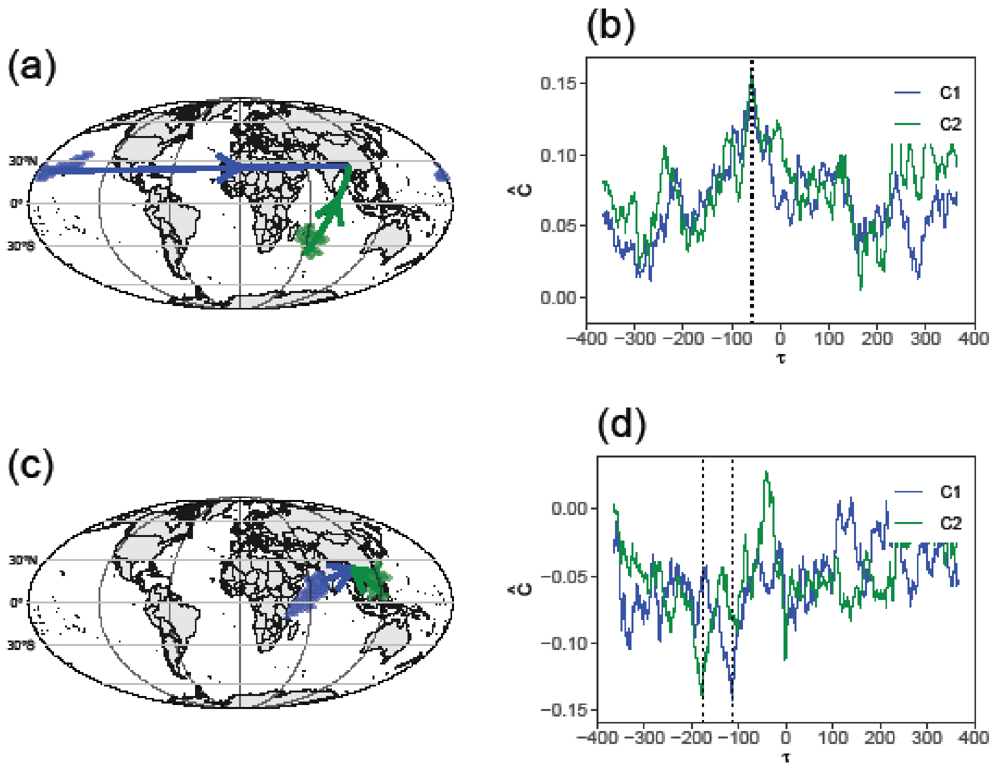

Figure 8. (Color online) Locations of the largest cluster C_1 (blue) and the second largest cluster C_2 (green) that are (a) positively ((c) negatively) correlated with the node I_{31} (I_{22}) in NWSA for JJA. Everything else is the same as Fig. 6.

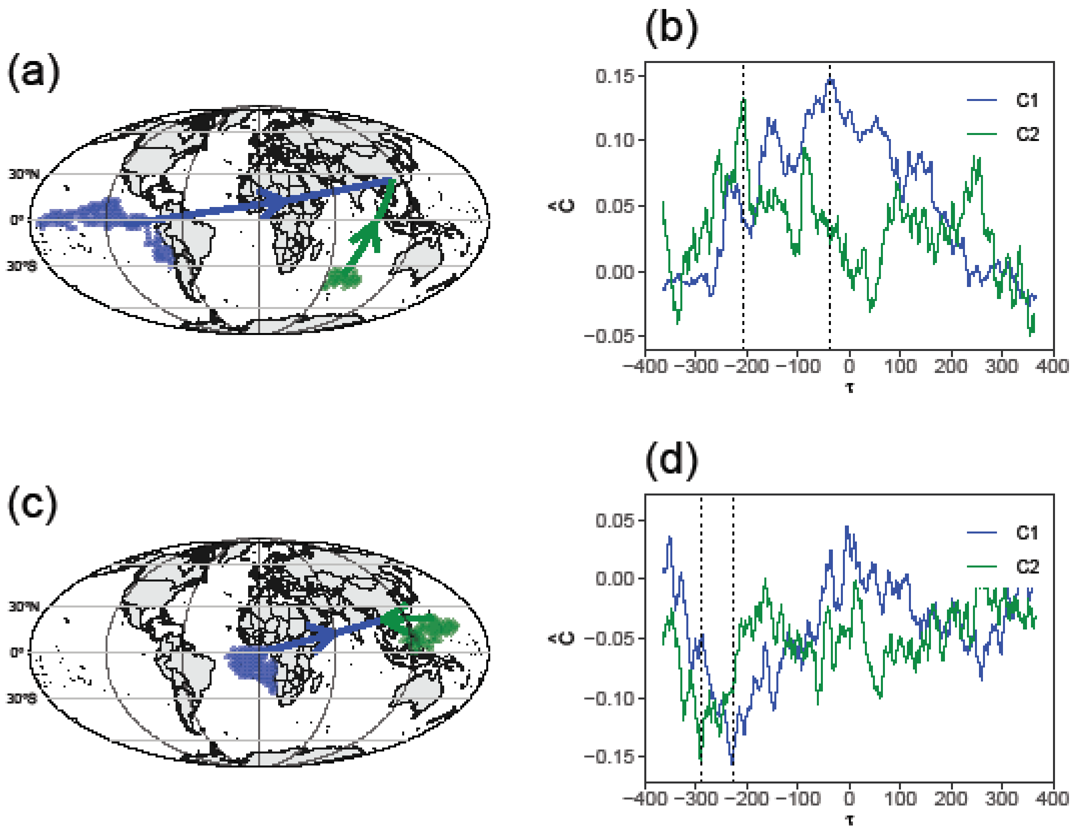

Figure 9. (Color online) Locations of the largest cluster C_1 (blue) and the second largest cluster C_2 (green) that are (a) positively ((c) negatively) correlated with the node I_{36} (I_{12}) in NWSA for SON. Everything else is the same as Fig. 6.