

Analyzing extreme temperatures in the United States using complex network theory

by

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Abstract

Extreme temperature events (ETEs), such as recent severe heat waves, are one of the consequences of climate change and global warming. To better understand their complex behavior and forecast climate and/or hydrologic dynamics, understanding and investigating their spatial and temporal patterns are essential. We, therefore, analyzed ETEs over the Contiguous United States (CONUS) for both summer and winter seasons using complex network theory. For this purpose, the daily maximum and minimum temperature data were collected from the Climate Prediction Center (CPC) database. To determine the level of similarity between two geographic nodes, we employed the event synchronization method and constructed the network of ETEs. The constructed networks were then corrected for boundary effects. Network measures i.e., degree centrality (DC), betweenness centrality (BC), clustering coefficient (CC), mean geographic distance (MGD) and long-ranged directedness (LD) were determined to analyze complex patterns within each network. Based on the network measures, we found that the ETEs are more synchronized in winters than those in summers. In addition, the BC and LD revealed that California plays an important role in the large-scale propagation of ETEs during summers, while Texas and the eastern region of New Mexico during winters. Furthermore, the evolution of ETEs from 1979 to 2022 uncovered increasing and decreasing trends for the summer and winter seasons, respectively. We also detected teleconnections over the CONUS. By applying the Louvain method for community detection, we detected different communities in the network of extreme temperature events for the summer and winter seasons.

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Dedication

To my late brother, Funsho Bosikun, for bringing us (siblings) together in oneness, and encouraging us to be diligent and committed to our studies.

Chapter 1 - Introduction

Recent extreme temperature events, ETes, such as severe heatwaves, have been threatening surface and subsurface water resources as well as water availability at the global scale (AghaKouchak et al., 2020; Zampieri et al., 2016). They also have influential economic and social impacts (Lee et al., 2024; Wang et al., 2017). Therefore, their spatial and temporal analyses have been active subjects of research (Ban et al., 2017; Cheng et al., 2024; Islam et al., 2020; Tong et al., 2019). For reviews, see Grotjahn et al. (2016) and Horton et al. (2016).

Spatiotemporal analysis of extreme climatic and/or hydrologic events (e.g., heatwaves, floods, and drought) requires identifying their extreme values. In the literature, parametric approaches, such as block maxima (Papacharalampous et al., 2021) and peaks over threshold (Chen et al., 2023) as well as non-parametric techniques, such as 90, 95 and 99th percentiles (Sun et al., 2024) have been applied to detect extreme events. Although parametric approaches have more statistical foundation, non-parametric methods are easier to use (Liu et al., 2013). For instance, Scherer and Diffenbaugh (2014) used 1st and 5th percentiles of daily minimum temperature to identify extreme cold events and 95th and 99th percentiles of daily maximum temperature to detect extreme hot events in the United States. In another study, Sheridan and Lee (2018) defined extreme temperature events based on the 95th percentile to analyze trends across North America. However, neither Scherer and Diffenbaugh (2014) nor Sheridan and Lee (2018) applied complex network theory to analyze extreme temperature patterns.

The climate system is complex and composed of numerous sub-systems interacting non-linearly over a wide range of spatiotemporal scales. Therefore, a suitable approach to study it should accurately capture complexities in the climate system, its components and underlying

dynamics. A promising theoretic approach is complex network analysis from statistical physics (Barabasi, 2016). It is an effective methodology to quantify structures of complex systems based on statistical analysis of their topologies. Complex network theory has been successfully applied to reveal fundamental mechanisms underlying climate networks and systems (Fan et al., 2021; Ludescher et al., 2021) which led to the emergence of a new concept called climate network (Tsonis and Roebber, 2004). Climate networks are constructed based on spatiotemporal analysis of climatic data or their extreme time series collected at various geographic locations (also known as nodes). The topology of complex networks reveals whether or not nodes have similar dynamic process characteristics. Analyzing their topology also allow exploring climate patterns or even forecasting extreme events (Boers et al., 2019; Boers et al., 2014).

There exist three main methods widely used to quantify similarities among nodes and link them within a climate network. First method is based on the Pearson correlation coefficient. In this approach, the Pearson correlation is used for the cross-correlation analysis between any two time or extreme event series. For instance, Steinhäuser et al. (2012, 2011) constructed climate networks to study how different climate variables such as sea surface temperature, sea level pressure, geopotential height, precipitable water, relative humidity, and wind speed are interrelated in time and space. They determined similarities among nodes by calculating the Pearson correlation coefficient. They found that the relationships among these climate variables can help improve understanding of climate dynamics and make better predictions about regional climate patterns. Second method is event synchronization (Quiroga et al., 2002). It is based on relative timings of events and measures synchronization between two event series. For example, Malik et al. (2012) used event synchronization to measure similarities in time series and analyze

extreme precipitation events in Indian Monsoon System. Boers et al. (2013) applied event synchronization and complex network analysis to characterize extreme precipitation synchronicity in the South American Monsoon System. Konapala and Mishra (2017) used event synchronization to study the spatiotemporal evolution of drought in 344 climatic divisions of the Contiguous United States. Third method is edit distance (Levenshtein, 1966), which was originally developed to measure similarity between two strings. As an example, Agarwal et al. (2022) used the edit distance approach to analyze extreme precipitation events in the Ganga River basin.

Extreme temperature events (ETEs) have exhibited a notable impact on human mortality (Smith and Sheridan, 2019) as well as substantial changes in frequency and intensity in the contiguous United States (CONUS) in recent decades (Sheridan and Lee, 2018). Both extreme heat and cold events pose potential ecological risks to many species (Vasseur et al., 2014) and can alter natural community structure through impacts on health (Sheridan and Allen, 2015) as well as energy consumption (Santamouris et al., 2015). Despite recent successful applications of network science to the climate system (Fan et al., 2021; Ludescher et al., 2021), the analysis of temperature and its extreme events via complex network theory has been limited, particularly within the United States. For instance, Mondal and Mishra (2021) investigated network structure and propagation characteristics of heatwaves over the contiguous United States in summers using complex network theory and daily maximum temperature. They identified source and sink regions, primarily responsible for heatwave propagations, and their interactions. In another study, Li et al. (2022) applied complex network theory to study temperature regionalization in China using hourly temperature data available at 2m above the surface. Links were detected based on correlations in temperature time series (Pearson

correlation coefficient $|R| \geq 0.9$ p-value < 0.01). Those authors determined degree centrality, geographic distance, and average node distance and found a few teleconnections within temperature network. However, Li et al. (2022) did not correct their constructed networks to account for boundary effects.

The main objectives of this study, therefore, are to: (1) investigate extreme temperature events using complex network theory, (2) analyze spatiotemporal patterns and ETEs propagations across the contiguous United States for both summer and winter seasons, (3) apply the event synchronization method to determine the level of similarity between any two geographic locations (nodes), (4) address the effect of bounding temporal delay between synchronous events within the event synchronization method, and (5) detect community structures and synchronization regimes as well as local-scale extreme temperature patterns.

Chapter 2 - Temperature data and their extreme values

The dataset used in this study is the Climatic Prediction Center (hereafter CPC) Global Unified Temperature data provided by the NOAA/OAR/ESRL PSD, USA. This dataset available at <https://psl.noaa.gov> contains daily grided minimum and maximum temperatures with temporal coverage from 1979 to 2022 and spatial coverage with resolution $0.5^\circ \times 0.5^\circ$ and a latitude ranged from 89.75N to 89.75S and a longitude from 0.25E to 359.75E. In the CPC database, there exist 3276 grid points within the CONUS. Each grid point includes time series of minimum and maximum daily temperatures. We should point out that one grid point contained a substantial number of missing values, and thus, we removed it from further analyses.

To construct the complex networks, we selected the temperature data from the CPC database for both summer (June, July, and August; hereafter JJA) and winter (December, January, and February; hereafter DJF) seasons. For the summer seasons, we analyzed the maximum temperature data and defined the ETEs as events whose values exceeded a threshold, set equal to 95th percentile (Konapala and Mishra, 2017). For the winter seasons, we used the minimum temperature data and defined the ETEs as those with values below the 5th percentile (Plavcová and Urban, 2020). The threshold at each grid point was calculated based on the 5th and/or 95th percentile, and the magnitude of each extreme temperature event was replaced with one. The ETEs on consecutive days were replaced with one single event on the first day (Boers et al., 2019). After determining the ETEs, we constructed the temperature networks based on the ETE series, as we describe in the next section.

Chapter 3 - Complex network analysis

The nodes in the temperature networks were the grid points on the Earth's surface. The link between any two nodes was determined based on the level of similarity between their ETE series quantified using the event synchronization (ES) method, as described in the following.

3.1 Event synchronization

There exist various approaches to determine the degree of synchronicity between two time series, such as Pearson correlation (Peron et al., 2014) and edit distance (Jamali et al., 2023). Among them, the event synchronization (ES) method, developed by Quiroga et al. (2002), was broadly employed to study extreme events (Boers et al., 2013; Malik et al., 2012; Mondal and Mishra, 2021; Sun et al., 2018a) and to determine links in the complex networks of ETEs. In this section, we briefly describe the ES method.

Let us assume two grid points i and j with series of length N_i and N_j i.e., $\{x_u^i\}_u^{N_i}$ and $\{x_v^j\}_v^{N_j}$. Two events on such series would be synchronous if they are closer to each other than their neighboring events. More specifically, event x_u^i would be synchronized with event x_v^j , if the absolute value of their temporal delay, $\Delta_{u,v}^{i,j} = x_v^j - x_u^i$, would be less than a local time scale $\tau_{u,v}^{i,j}$ defined as:

$$\tau_{u,v}^{i,j} = \frac{1}{2} \min\{\Delta_{u,u-1}^{i,i}, \Delta_{u+1,u}^{i,i}, \Delta_{v,v-1}^{j,j}, \Delta_{v+1,v}^{j,j}\} \quad (1)$$

In Figure 1, we schematically demonstrate the ES method. Unlike the static delay used in the correlation approach, the local time scale, $\tau_{u,v}^{i,j}$, known as the dynamical delay varies based on the events in consideration (Meng et al., 2018). To avoid unrealistic synchronization due to long dynamical delays, the temporal delay, $\Delta_{u,v}^{i,j}$, is constrained by a lag time τ_{max} as proposed by Quiroga et al. (2002). This adjustment helps prevent events from being inaccurately considered

synchronized when the dynamical between them is too large. The number of synchronous events between two event series i and j that satisfy the condition $|\Delta_{u,v}^{i,j}| < \tau_{u,v}^{i,j}$ and $|\Delta_{u,v}^{i,j}| \leq \tau_{max}$ is then denoted as $ES^{i,j}$.

In the ES method, τ_{max} bounds the temporal delay between synchronous events. Therefore, its value affects the construction of complex networks. Depending on the time scale of interest, one may set τ_{max} equal to zero or any other positive number. By setting $\tau_{max} = 0$, only events happened on the same day would be considered synchronized (Boers et al., 2014). To address the effect of τ_{max} on the complex networks of ETEs, in this study we tried different values i.e., $\tau_{max} = 0, 1, 3, 4, 5$ and 10 days (Boers et al., 2019; Gupta et al., 2023). We present the results for $\tau_{max} = 0$ and $\tau_{max} = 10$ here, while results for the other τ_{max} values are included in the Appendix.

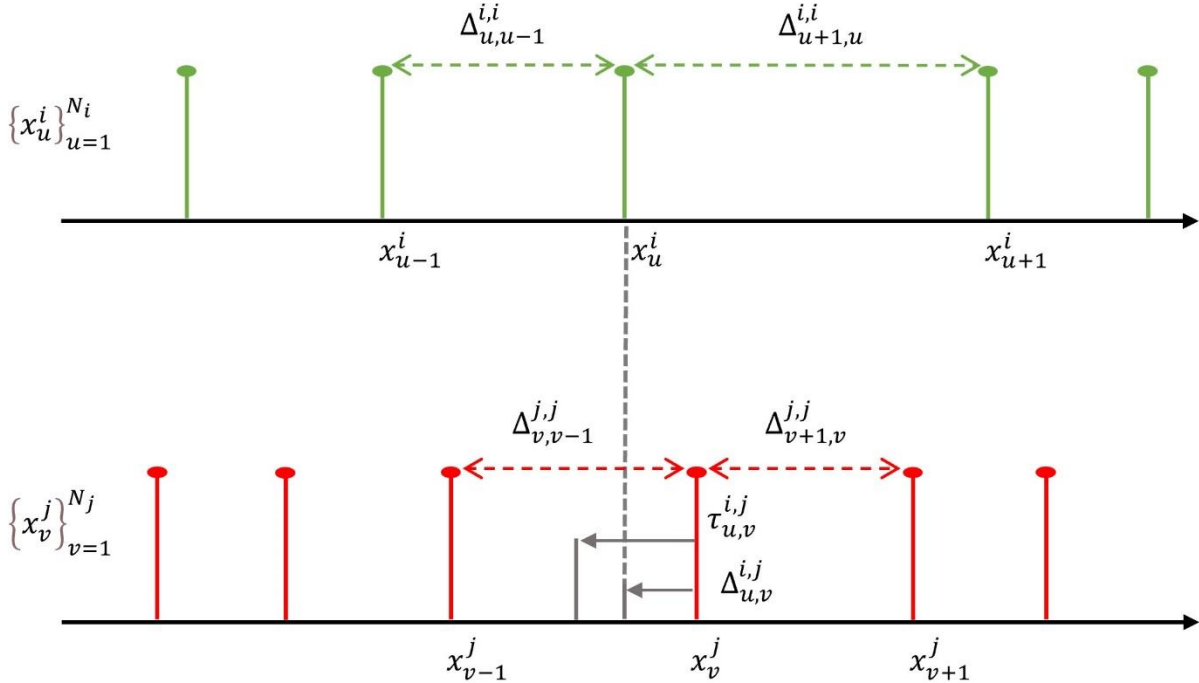


Figure 1. Scheme of the event synchronization method in which event x_u^i would be synchronous with event x_v^j , if the absolute value of their temporal delay $\Delta_{u,v}^{i,j} = x_v^j - x_u^i$, is less than a local time scale $\tau_{u,v}^{i,j}$.

3.2. Network construction

As stated earlier, we extracted the ETes from the temperature time series at each grid point and, accordingly, computed the level of similarity, S , between any two grid points. After that, we linked nodes i and j , if their similarity, S^{ij} , was statistically significant. We compared S^{ij} with a null-model distribution of S based on an ensemble of 3000 pairs of randomly shuffled versions of the event series $\{x_u^i\}_{u=1}^{N_i}$ and $\{x_v^j\}_{v=1}^{N_j}$ (Boers et al., 2019). The ETes series were randomly shuffled to change the temporal positions of ETes, and the 99.5th percentile of the null distribution was applied as the significance threshold S_{thresh}^{ij} (Boers et al., 2019). If $S^{ij} > S_{thresh}^{ij}$, we connected nodes i and j . The adjacency matrix A was generated for summer (JJA) and winter (DJF) seasons to represent the constructed complex networks of ETes and to measure various network measures, as we explain in the next section. In the adjacency matrix, $A_{ij} = 0$ indicates no link between nodes i and j , while $A_{ij} = 1$ denotes the two nodes are connected.

3.3. Network measures

To analyze the constructed complex networks of ETes, we calculated five network measures i.e., degree centrality (DC), betweenness centrality (BC), clustering coefficient (CC), mean geographic distance (MGD), and long-ranged directedness (LD) from their adjacency matrices.

The DC is a node-based measure and indicates the number of links connecting one node to others within the complex network of ETes. It is defined as

$$DC_i = \sum_{j=1}^n A_{ij}. \quad (2)$$

The higher the DC , the more the large-scale synchronizations and teleconnections would be (Agarwal et al., 2022b; Sun et al., 2018b).

The BC is based on shortest geodesic paths in the complex network. Its value at a node is the sum of the fraction of the shortest paths passing through a node to the total number of shortest paths connecting any pair of nodes. It is given by (Sun et al., 2018b)

$$BC_j = \frac{\sum_{k,l \neq j} \sigma_{kl}(j)}{\sum_{k,l \neq j} \sigma_{kl}} \quad (3)$$

where σ_{kl} is the number of shortest paths between k and l , and $\sigma_{kl}(j)$ is the number of shortest network paths passing through j . A grid point with high BC value significantly contributes to the propagation of extreme events, particularly over large spatial distances (Boers et al., 2013).

The CC quantifies interconnectivity among neighbors within a network. It is the number of the neighbors of a particular grid point that are also connected to one another. The CC at the i^{th} grid point is defined as

$$CC_i = \frac{\sum_{j < k} A_{ij} A_{jk} A_{ik}}{\sum_{j < k} A_{ij} A_{ik}}. \quad (4)$$

A region with high CC values exhibits rather large spatial coherence (Boers et al., 2013).

The MGD represents the average spatial distance at which a node is synchronized with others and given by (Boers et al., 2013)

$$MGD_i = \frac{1}{DC_i} \sum_{j=1}^n D_{ij} A_{ij} \quad (5)$$

where D_{ij} is the geographic distance between nodes i and j . High MGD values imply synchronization with distant nodes indicating long-range connections (or teleconnections), while low values short-range connections (or regional connections).

One may describe ETE characteristics in a geographic location from regionally clustered to long-ranged and directed using the LD , which is determined from other network measures i.e., BC , MGD , and CC (Boers et al., 2013). This metric depicts complementary characteristics of a

complex network. Compared to other network measures, the LD offers significantly more robust and thorough insights into underlying mechanisms of a complex system. The LD is defined as

$$LD = 1/2 BC + 1/2 MGD - CC \quad (6)$$

To determine the LD via Eq. (6), the normalized values of BC , MGD , and CC were used (Boers et al., 2013). Within a region of low LD value due to low BC and MGD and high CC values, ETEs occur spatially coherently (and extensively within that region) with minimal long-range effects. However, in a region of high LD values due to high BC and MGD and low CC values, ETEs are likely associated with dynamic and directed air mass transport processes over a constrained pathways and spanning extensive spatial distances (Boers et al., 2013).

3.4. Boundary effect corrections

Complex networks of ETEs are spatially embedded networks whose nodes are geographic locations on the Earth's surface. In this study, only those nodes inside the CONUS were used. This may cause significant spatial biases in the network measures, particularly near the boundaries. Therefore, the constructed networks should be corrected to remove such biases. For this purpose, we applied the approach developed by Rheinwalt et al. (2012). For this purpose, we first generated an ensemble of random surrogate versions of the original network. We then corrected all network measures by dividing them by their expected values of the corresponding ensembles. We should note that we determined the surrogate networks from randomly changing the links within the original network, while we preserved the link probabilities and the degree centrality probability density function.

3.5. Community detection

Partitioning a network into different groups based on the density of links is called community detection. Nodes within a community are more connected to each other than outside nodes. In other words, the interconnectivity within communities shows a higher density than the connectivity between distinct communities. Using the community detection, one would be able to identify underlying components of a network, categorize nodes, examine propagation dynamics across a network, and mitigate the problem of missing links (Fortunato, 2010; Fortunato and Hric, 2016). Within the domain of complex network theory, community detection entails reconfiguration of the elements of the adjacency matrix to form an approximate block diagonal structure. In the literature, there are different approaches for community detection, such as graph partitioning, hierarchical clustering, divisive algorithms, and modularity-based methods (Webber and Marwan, 2015). In this study, we used the Louvain method (Blondel et al., 2008), proposed for large networks, in which the following a modularity function is optimized (Newman, 2004)

$$M_f = \frac{1}{l_t} \sum_{c=1}^{n_c} \left(l_c - \frac{d_c^2}{4l_t} \right) \quad (7)$$

where n_c is the number of communities, l_c and d_c are the number of links and the total degree of the nodes inside the c^{th} community, respectively, l_t is the total number of links, and $\frac{d_c^2}{4l_t}$ is the expected number of links within the c^{th} community, if the network links are randomly surrogated with the degree of the nodes remaining the same.

Through community detection, a network should be partitioned by maximizing the M_f in Eq. (7), which becomes computationally demanding in large networks. Alternatively, approximation algorithms (Brandes et al., 2008), such as the Louvain method, are applied. For instance, the Louvain method, based on the principles of graph theory, is a proficient hierarchical

clustering technique, which aims to maximize the modularity of a community division by iteratively repositioning nodes until an optimal community partition is achieved (Zhang et al., 2021). In this method, prior knowledge of the number of communities is not required (Blondel et al., 2008). We should point out that results of the Louvain method may be subjected to slight variations, even if repeated using the same parameters, due to its inherent probabilistic nature. To minimize such uncertainties, we used the consensus clustering post-processing technique (Lancichinetti and Fortunato, 2012). For this purpose, the community detection was first repeated 100 times and a matrix composed of elements showed how many times two nodes in the same community was then constructed. After that, the constructed matrix was converted into an adjacency matrix using a threshold of 0.5. This process was repeated until a state of stability was achieved, signifying no alterations in the identified communities. For the community detection, we used the Louvain community detection library available in NetworkX (Hagberg et al., 2008). We set weight equal to 1, because the constructed complex networks of ETEs were unweighted, resolution equal to 1, threshold equal to 0.5.

Chapter 4 - Results and Discussion

In this section, we present the obtained results and discuss them in detail. We first describe the trends in the ETEs determined for both summer and winter seasons and analyze how the ETEs have evolved over four decades (1979-2022) due to climate change and global warming. We then present the results of complex network analysis within the CONUS.

4.1. Trends in extreme temperature events

The mean surface temperature across the globe has been consistently rising up since the 70's (Rahmstorf et al., 2017). With climate change and global warming impacts, one question is “How has the number of extreme temperature events been changing over the past several decades?” The general expectation is an increase in the number of ETEs in summers and a decrease in the number of ETEs in winters due to global warming.

To answer the above question and to analyze the evolution of ETEs in the CONUS, we analyzed trends in the number of ETEs for both summer and winter events. Figure 2 shows the number of ETEs as a function of time from 1979 to 2022. The fit of the linear function is also shown. For the JJA, we found an increasing trend in the ETEs with a positive slope equal to 2.55, $R^2 = 0.17$ and p-value = 0.0052. For the DJF, however, the trend is decreasing with a negative slope equal to -1.33, $R^2 = 0.05$ and p-value = 0.1263. The low R^2 values are due to scatters in the data. For the summer season (JJA), the low p-value (< 0.05) indicated statistically that the slope of 2.55 was significantly different from zero at the 0.95 confidence level. However, for the winter season (DJF) the p-value was greater than 0.05, which showed that the slope of -1.33 was not significantly different from zero. These results clearly demonstrate the notable effect of climate change and global warming on the ETEs in the CONUS over four decades.

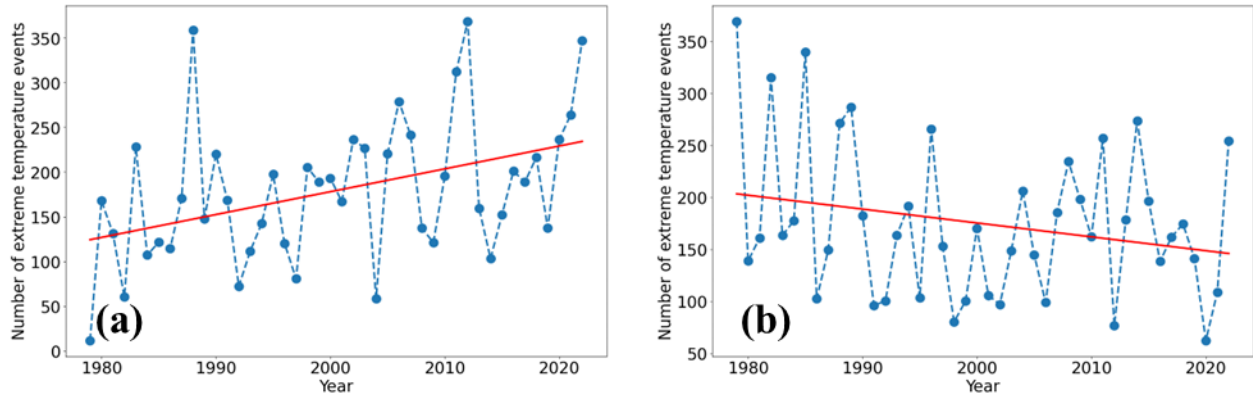


Figure 2. The number of ETEs per season over the CONUS from 1979 to 2022 for the (a) summer (JJA) and (b) winter (DJF) seasons. The solid lines represent the linear function fitted to the data. The slope of the solid line of the fit is 2.56 (with $R^2 = 0.17$) for the JJA and -1.33 (with $R^2 = 0.05$) for the DJF.

Note that the values on the vertical axis are the number of ETEs divided by the length of the year (which in this case is 44).

The trends in the ETEs shown in Figure 2 are also in agreement with those reported by Sheridan and Lee (2018) for the 1979–2016 period. Following Nairn and Fawcett (2014), they defined extreme heat events as when excess heat factor exceeded the 85th percentile of all positive extreme heat values for a region over a time frame. In their study, the excess heat factor was defined as the product of (1) the magnitude of heat event and (2) acclimatization factor. The former was defined when the daily mean temperature averaged over a three-day period was above the 95th percentile of daily mean temperature, and the latter as the difference between a recent three-day mean apparent temperature and the average apparent temperature over the preceding 30 days. To determine extreme cold events, Sheridan and Lee (2018) calculated excess cold factor in a similar way using the threshold of 15th percentile. They reported an increasing trend in extreme heat events across the United States and Canada as well as a decreasing trend in extreme cold events.

Figure 2a also shows substantial number of ETEs in years 1980, 1988, 1998, 2003, 2012 and 2022 corresponding to severe heat waves in the US (Lott and Ross, 2006; Lyon and Dole, 1995; NOAA, 2022). Damage costs in 1988 was estimated to be in the range of 30.2 to 57.7 billion US dollars with 454 direct and 5,000–10,000 excess deaths (Keellings and Moradkhani, 2020). In 1998, costs were approximated to be around 6.6 to 9.9 billion US dollars with at least 200 deaths (Lott and Ross, 2006). Estimated damage cost was 31.5 to 38.2 billion US dollars in 2012 (Keellings and Moradkhani, 2020) and 22 billion US dollars in 2022 (NOAA, 2022).

Similar to Figure 2a, the trend in the evolution of ETEs in winters (Figure 2b) indicates significant year-to-year fluctuations. Figure 2b also captures the cold extremes of 1989, 2011, 2014 and 2022. Record low temperature in 1989 impacted various states, such as Kansas, Missouri, Nebraska, and North Carolina in the CONUS (Erdman, 2024), and cold snap was experienced in Texas (Doss-Gollin et al., 2021). Additionally, there was another cold snap occurrence in Texas and the Southwest region of the United States in 2011, which severely affected particularly the natural gas and electric sectors (Gardner, 2012). The December 2013 to February 2014 period was recorded as one of the coldest winters in the Great Plains and parts of the Midwest (Erdman, 2016). In November and December 2022, extreme cold wave hit the United States which led enormous social and economic damage and one of the coldest Christmas in about 40 years (Yao et al., 2023).

4.2. Temperature data analysis

To obtain some insights about general patterns of temperature in the CONUS, we analyzed the temperature time series for both summer and winter seasons. In Figure 3, we show the average minimum and maximum temperatures, 5th and 95th percentiles, and spatial distribution of the number of ETEs for the JJA and DJF. As can be seen, on an average, Southern

US often experiences higher temperatures in the summer and winter seasons than the Northern US (Figures 3a and 3b).

Figures 3c and 3d show the threshold values used to define the ETEs in this study. These maps are similar to the average temperature maps presented in Figures 3a and 3b. Such general similarities were also observed by Jamali et al. (2023) who analyzed precipitation data over the CONUS. High thresholds were observed in the Southern US, particularly southwest, for the summer season, while low thresholds in the Northern US, particularly northeast, for the winter season. Figures 3e and 3f show the spatial distribution of the number of ETEs within the CONUS for the summer (JJA) and winter (DJF) seasons, respectively. As can be observed, the highest number of ETEs happen in the Northern US during the summer season (Figure 3e). Elevated occurrences of extreme temperature events (>105) are noticeable along the west coast of Washington and California, the southwestern region of Arizona and southern Florida. Similarly, high occurrences of ETEs were noted near Lake Michigan and the far Northeastern regions of the CONUS. Our Figure 3e, to some extent, exhibits similarities to the average number of heatwave days reported by Mondal and Mishra (2021), particularly in the southeastern and western regions of the CONUS (see their Figure 1c). The lowest number of ETEs was observed in the south-central regions of the CONUS. Interestingly, previous studies (Alexander et al., 2006; Coumou et al., 2013; Kunkel et al., 2006; Pan et al., 2004) reported cooling trends in temperature extremes termed “warming whole” in the south-central/southeastern region of the CONUS. While some of these studies detected the warming hole in the southeastern United States, others found it in the central United States depending on the dataset analyzed and time interval (Portmann et al., 2009).

For the winter season, the eastern regions of the CONUS have higher number of ETEs than the western ones. Notably, lower number of ETEs can be observed in the northwestern regions extended to Utah. This agrees with the findings of Easterling (2002) who reported that there have been proportionately more decreases in observed frost days (defined as daily minimum temperature below freezing) in the western CONUS compared to eastern CONUS.

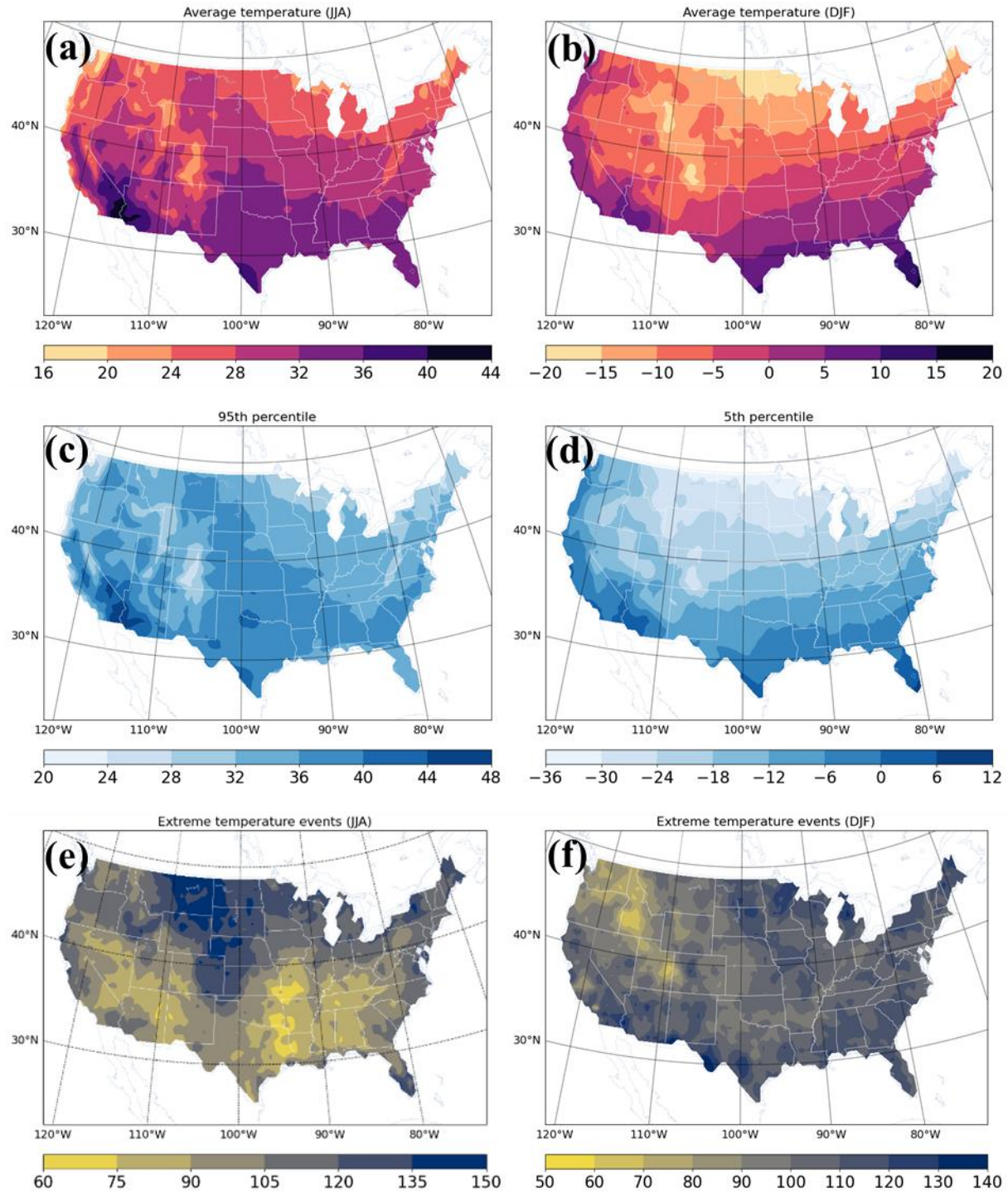


Figure 3. Average maximum and minimum temperature (top), thresholds based on the 95th and 5th percentiles (middle) and number of ETEs (bottom) within the CONUS from 1991 to 2022. The left and right plots correspond to the summer (JJA) and winter (DJF) seasons respectively.

4.3. Complex network analysis of extreme temperature events

In this section, we present the results of complex network analysis of ETEs over the CONUS. Results are presented for $\tau_{max} = 0$ and 10 days here and for other τ_{max} values in the Appendix. Note that for network construction, we used data from 1991 to 2022.

- Degree centrality

The DC of a grid point, computed using Eq. (2), denotes the number of its neighbors linked via synchronized ETEs. Results of the DC for the grid points within the CONUS are shown in Figure 4 for the summer and winter seasons and $\tau_{max} = 0$ and 10 days after correcting for the boundary effects. Recall that $\tau_{max} = 0$ corresponds to ETEs synchronized on the same day, while $\tau_{max} = 10$ to those synchronized within 10 days. We should point out that after boundary effects correction, the network measures were normalized and, thus, ranged between zero and one.

For the JJA, the largest values of DC were observed in the northeast of the CONUS (Figures 4a and 4b). For $\tau_{max} = 0$ day, Appalachian Highlands in the Northeast, regions near Lake Michigan, southern California, northern Montana and southwestern Arizona had the highest DCs (Figure 4a). For $\tau_{max} = 10$ days, however, the hubs were mainly restricted to the far northeastern region (including Maine, Massachusetts and New Hampshire) and southern California (Figure 4b). Such regions of large DCs act as hubs (also known as supernodes), nodes with numerous links (Tsonis et al., 2006), and play a crucial role in teleconnections and large-scale communication within the structure and dynamics of complex systems (Mondal and Mishra, 2021; Pei and Makse, 2013). Regardless of the τ_{max} value, the northeast region exhibits the highest DCs (see Figure 15 in the Appendix). Interestingly, Jamali et al. (2023), who analyzed extreme precipitation events in the CONUS, also found hubs in the northeast of the US

for the summer season (see their Figure 4a). This may be due to urban heat island effect (Allen and Sheridan, 2016; Habeeb et al., 2015; Zahn et al., 2021). As can be seen from Figure S1, by increasing the τ_{max} regions with lower DC values grew in size because less events were synchronized. To the best of our knowledge, this is the first study demonstrating the effect of τ_{max} in the ES method on the complex network analysis of ETEs in the CONUS.

For the summer season and $\tau_{max} = 0$ day, we found the smallest DCs mainly along the west, south and southeast coasts as well as West South Central of the CONUS (Figure 4a). For $\tau_{max} = 10$ days, however, those regions were extended to South Atlantic, East South Central, West North Central and Pacific in the US (Figure 4b). Summer extreme temperature events, such as heatwaves, in the coastal regions exhibit distinctive patterns and are highly localized and, thus, may not have strong connections with heatwaves occurring further inland (Mondal & Mishra, 2021). This suggests that factors influencing coastal heatwaves, such as local weather patterns and sea-land interactions may be different from those impacting heatwaves in inland areas. This could be because inland thermal low might restrict warm air masses coming from the Gulf of Mexico and the Atlantic Ocean to propagate farther into the interior land areas (Lee and Grotjahn, 2016). Nevertheless, the presence of westerly wave fluxes and the prevailing subsidence condition could result in persistent heating and horizontal heat advection in the coastal areas of the western United States (Lee and Grotjahn, 2016), which might result in the widespread propagation of warm air mass into inland regions. Using the 1979-2018 data from the CPC database and for the warm season of May to September, Mondal and Mishra (2021) reported highest DCs in the northwest part of the CONUS and near Michigan Lake, and the lowest DCs near the coastal regions of CONUS (see their Figure 2a).

For the DJF and $\tau_{max} = 0$, we detected the hubs in the northeast and northwest of the CONUS as well as south Florida, Texas and east New Mexico (Figure 4c). For $\tau_{max} = 10$ days, however, we observed the hubs in south Texas as well as northeast including the Appalachians (Figure 4d). Detecting hubs in Texas during the winter season is not surprising as Texas has been under the influence of cold snaps in the past (Doss-Gollin et al., 2021). Comparing the results for $\tau_{max} = 0$ day (Figure 4c) with those for $\tau_{max} = 10$ days (Figure 4d) indicates that some nodes in regions such as Texas, Florida and northwest became less connected as τ_{max} increased from 0 to 10 days, although some nodes in northeast became more connected. For $\tau_{max} = 0$ and 10 days, the lowest DCs are found in the southwest particularly in Arizona, New Mexico and California, and the Mountain West regions in Nevada, Utah and western Colorado; suggesting less synchronization of cold extremes (ETEs in winter) with other regions.

Note that the high DCs observed in south Florida at 0-day time lag disappeared at higher time lags, and the pattern of the DCs is different for various time lag (Figure 16 in the Appendix), which implies that the time lag affects the pattern of the degree centrality.

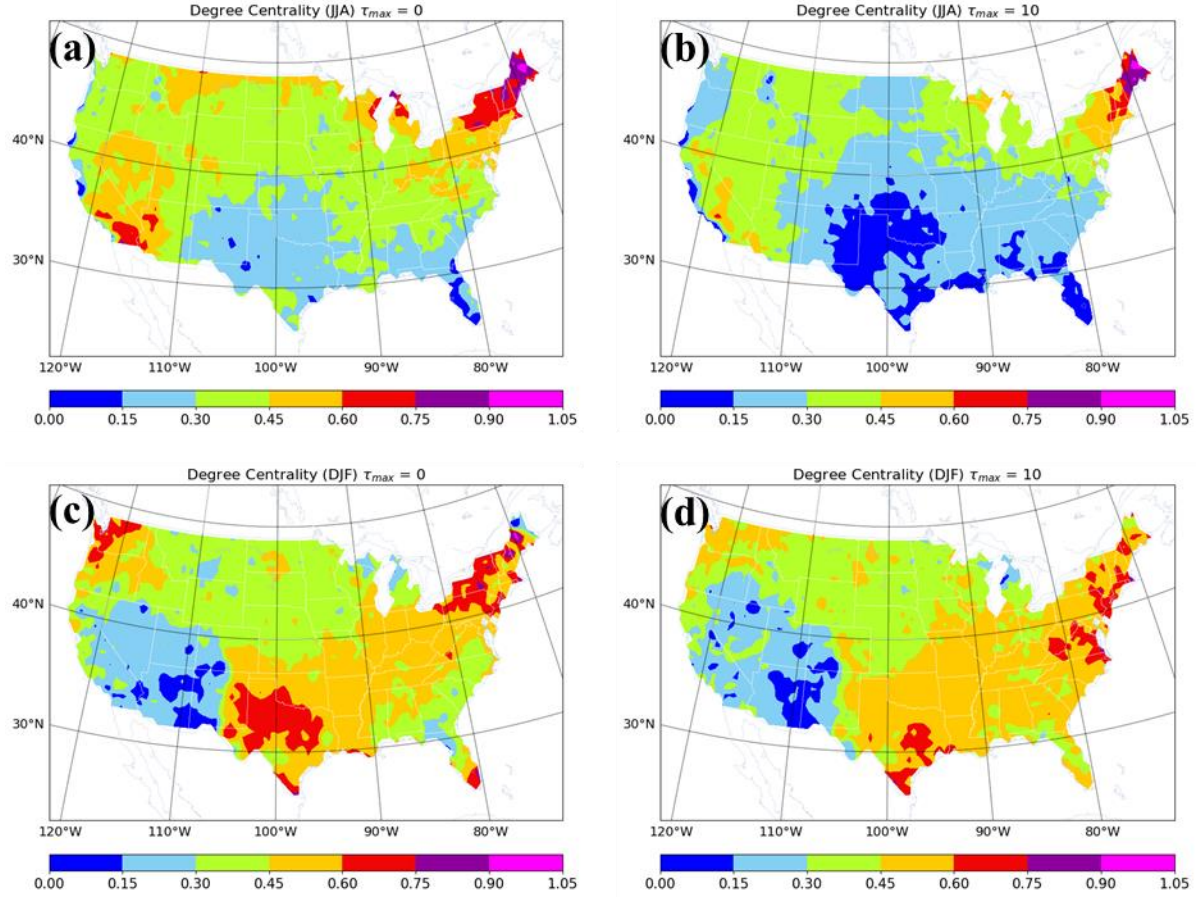


Figure 4. Normalized degree centrality, DC, for summer (a)-(b) and winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days. DC maps corresponding to other τ_{max} values are presented in Figure 15 for the summer season and in Figure 16 for the winter season in the Appendix.

- Mean geographic distance

The spatial patterns of the synchronization scale or distance of ETEs over CONUS can be assessed by determining the mean geographic distance (MGD), another node-based network measure. Identifying grid points with high MGDs is crucial, particularly to detect teleconnections. We computed the value of MGD using Eq. (5). The normalized MGDs after correcting for boundary effect are displayed in Figure 5 for both JJA and DJF seasons. Note that the MGD becomes dimensionless after removing the boundary effect. In Figure 5, regions with

low values indicate the areas with short-range synchronizations, while high values denote those with long-range synchronizations or teleconnections.

For the JJA season and $\tau_{max} = 0$ day (Figure 5a), the highest MGD values corresponding to teleconnections were observed in the northeast, southeast Florida, southeast Texas and west coast (southwest and northwest) as well as Lake Michigan in the CONUS. For $\tau_{max} = 10$ days, the largest MGD values were mainly found in the northeast of CONUS (Figure 5b), similar to the results of DC shown in Figure 4b. Additionally, some regions near the west coast, from eastern Arizona over the Sierra Nevada to northern California, as well as near the Lake Michigan had also large MGDs (greater than 0.60). No large MGDs were found in the southern regions, such as Florida and Texas (Figure 5b), unlike the MGD results for $\tau_{max} = 0$ day (Figure 5a). Comparing Figures 5a and 5b demonstrate that the choice of time lag (τ_{max}) in the ES method affects the spatial pattern of the results. Depending on the temporal scale of interest for synchronization, one should choose a time lag to investigate spatial variations for a specific time scale.

Results of the MGD for $\tau_{max} = 0$ and 10 days and the winter season are presented in Figures 5c and 5d. As can be seen from Figure 5c, the largest MGD values were observed in the northwest and northeastern regions as well as the lower Great Plains in the south of the CONUS for $\tau_{max} = 0$ day. However, for $\tau_{max} = 10$ days we found the Pacific northwest through the Great Plains down to the south, and further to the eastern regions of CONUS with the largest MGDs (Figure 5d). In winter, cold air masses enter the CONUS through the north and traverse southward and often to the eastern regions (Colle and Mass, 1995). For both τ_{max} values, the smallest MGDs were seen in the west notably in the south of Mountain region. Results exhibited regional connections as well as teleconnections. Nodes with larger MGDs were more spatially

distributed during the DJF than those during the JJA, which might be due to larger atmospheric systems causing ETEs in winters.

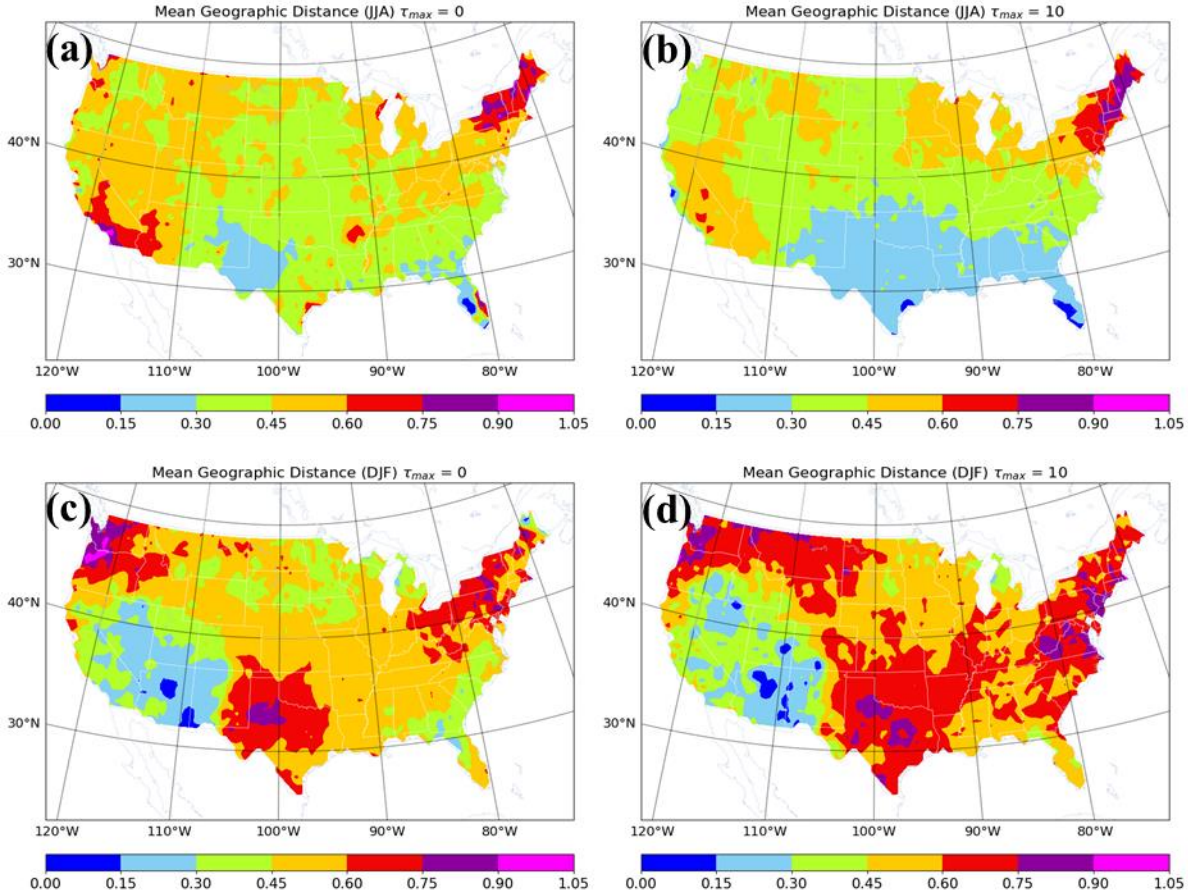


Figure 5. Normalized mean geographic distance, MGD, for summer (a)-(b) and for winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days.

We also investigated the regime shift from regional connection to large-scale teleconnections by analyzing the MGD distributions shown in Figure 6 for the JJA and DJF seasons as well as $\tau_{max} = 0$ and 10 days. Results for all τ_{max} values are shown in Figure S5 for the summers and in Figure S6 for the winters. For the summer season, we found a crossover in the MGD around either 3400 or 3600 km regardless of the τ_{max} value (Figure 12 in the Appendix). This means a regime shift from regional temperature system to large-scale

teleconnections existed. For the winter season, however, a crossover around 3400 km was observed at $\tau_{max} = 0$ and 1 days (Figure 13 in the Appendix). One possible explanation is that the regime shift from regional connection to large-scale teleconnection was not captured in winters at $\tau_{max} > 1$, which may be because here the study area was restricted to the CONUS, and, therefore, teleconnections that happened at the global scale were not captured.

By analyzing precipitation data over the CONUS using complex network approach, Jamali et al. (2023) investigated regime shift from regional connections and large-scale teleconnections and reported a crossover distance around 2600 and 2000 km for summers and winters, respectively. The former is close to the crossover distance of 2500 km reported by Boers et al. (2019) who analyzed precipitation data at the global scale during the summer season. Such crossover distances for precipitation at the semi-continental and global scales are shorter than those we found for the temperature and CONUS scale in this study. The reason why synchronization propagates easier within the ETE complex network than the extreme precipitation event one is a large low-pressure climate system, such as a mid-latitude cyclone, would lower temperature across it, while precipitation is limited to a more restricted zone.

Regarding the effect of τ_{max} on crossover distance, Boers et al. (2019) varied τ_{max} from 3 to 30 days and observed that the results of teleconnections were not sensitive (see their Extended Data Figure 6). Jamali et al. (2023) also found that crossover distance was not sensitive to the value of τ_{max} . They stated that the reason could be because by increasing τ_{max} the number of links corresponding to geographic distance near but smaller than crossover increased and consequently slopes before and after crossover became identical. In this study, we also found that the MGD distribution was nearly insensitive to the choice of τ_{max} (see Figures 12 and 13 in the Appendix).

We also investigated the correlation between the MGD and DC. Results presented in Figure S7 exhibited correlations with $0.63 < R^2 < 0.90$ for the summer season with smallest and highest correlations for $\tau_{max} = 0$ and 10 days, respectively. For the winter season, we found $0.86 < R^2 < 0.90$ with increasing trend in correlation from $\tau_{max} = 0$ to 1 day and decreasing trend from $\tau_{max} = 1$ to 10 days (Figure 14). A similar strong correlation was also reported by Mondal and Mishra (2021).

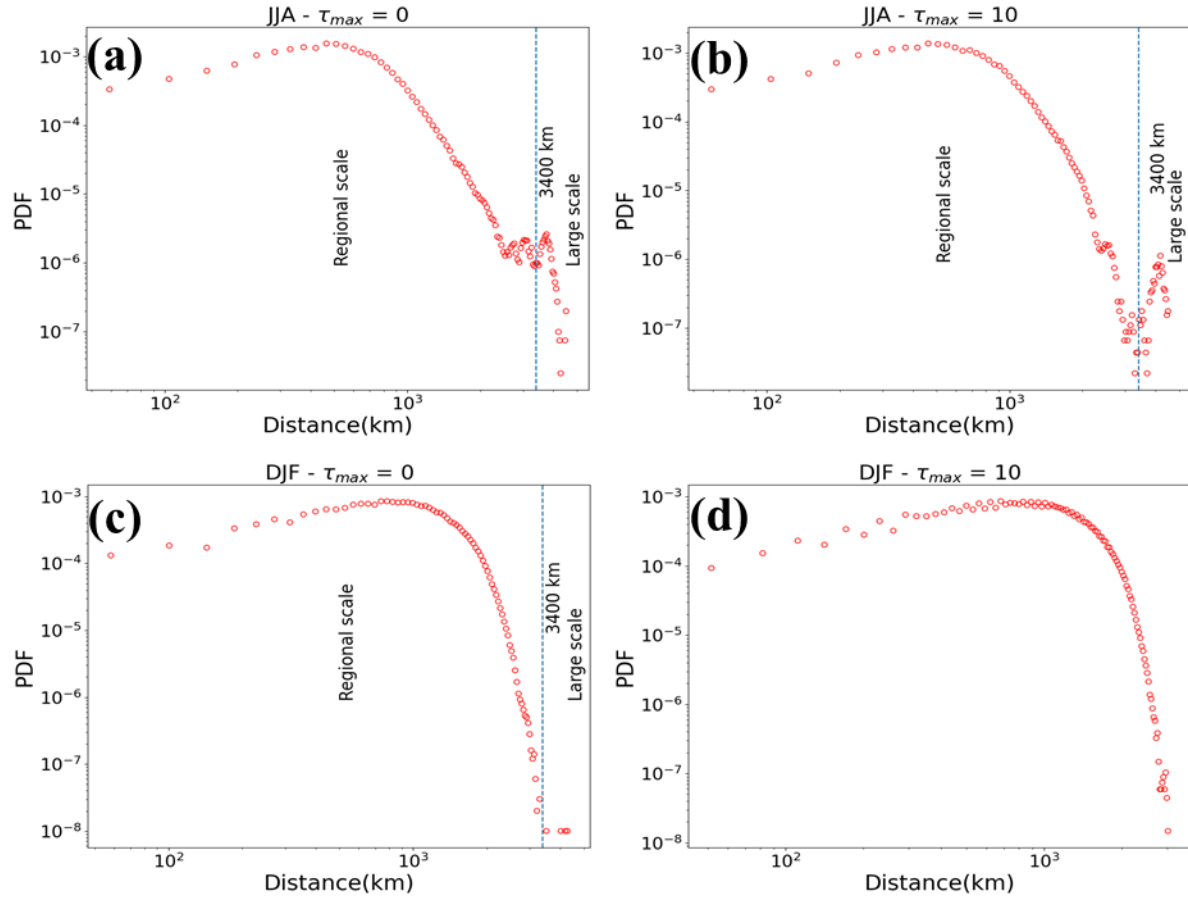


Figure 6. The geographic distance distributions of the connected grid points in the network of ETEs on logarithmic scales. The top plots, (a)-(b) are for the JJA season while the bottom ones (c)-(d) are for the DJF season. The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days.

- Clustering coefficient

The CC implies interconnectivities among the neighbors in the complex network of ETEs. Nodes with higher CCs are more likely to be spatially connected to their immediate neighbors, with less tendency to propagate to distant areas.

Results for the JJA season and $\tau_{max} = 0$ day revealed the largest CCs belonged to east Texas followed by high-altitude areas near the North American Cordillera and West North Central (Figures 7a). These regions have relatively small MGD (Figure 5a) and BC (Figure 8a) values compared to their neighboring areas. These imply that summer ETEs such as heatwaves are highly localized and more contained within the mountain regions of the Sierra Nevada, Rockies and Cascade Range (with large CCs), and less likely to synchronize and propagate widely to distant locations as evidenced by smaller MGD values relative to adjacent regions and small BC values (Mondal and Mishra, 2021).

As can be observed from Figure 7a, there is a pattern of large CCs over the Northern Great Plains and Midwest extended from the south of Lake Michigan to the Northern Great Plains at $\tau_{max} = 0$. However, this pattern is not seen when $\tau_{max} = 10$ days (Figure 7b). This suggests that ETEs like heatwaves in these regions are highly localized and will seldom propagate over to distant areas at $\tau_{max} = 10$ days.

For the DJF season, at $\tau_{max} = 0$, largest CC can be observed in the northern states Idaho, Montana, the Dakotas stretching to Wisconsin and Michigan (Figure 7c). Additionally, southern regions of the Carolinas, Georgia, Alabama and Florida displayed high clustering coefficient. At $\tau_{max} = 10$, the pattern of the large CC is such that it covers the state of Minnesota and spread through Michigan to the New York in the East. This further extends southward to Mississippi and north of Florida (Figure 7d). In both cases $\tau_{max} = 0$ and $\tau_{max} = 10$, large CC can be

observed in the Midwest regions of Minnesota, Wisconsin, Iowa and Michigan. Cold waves in these regions occur extensively and rarely impact distant areas.

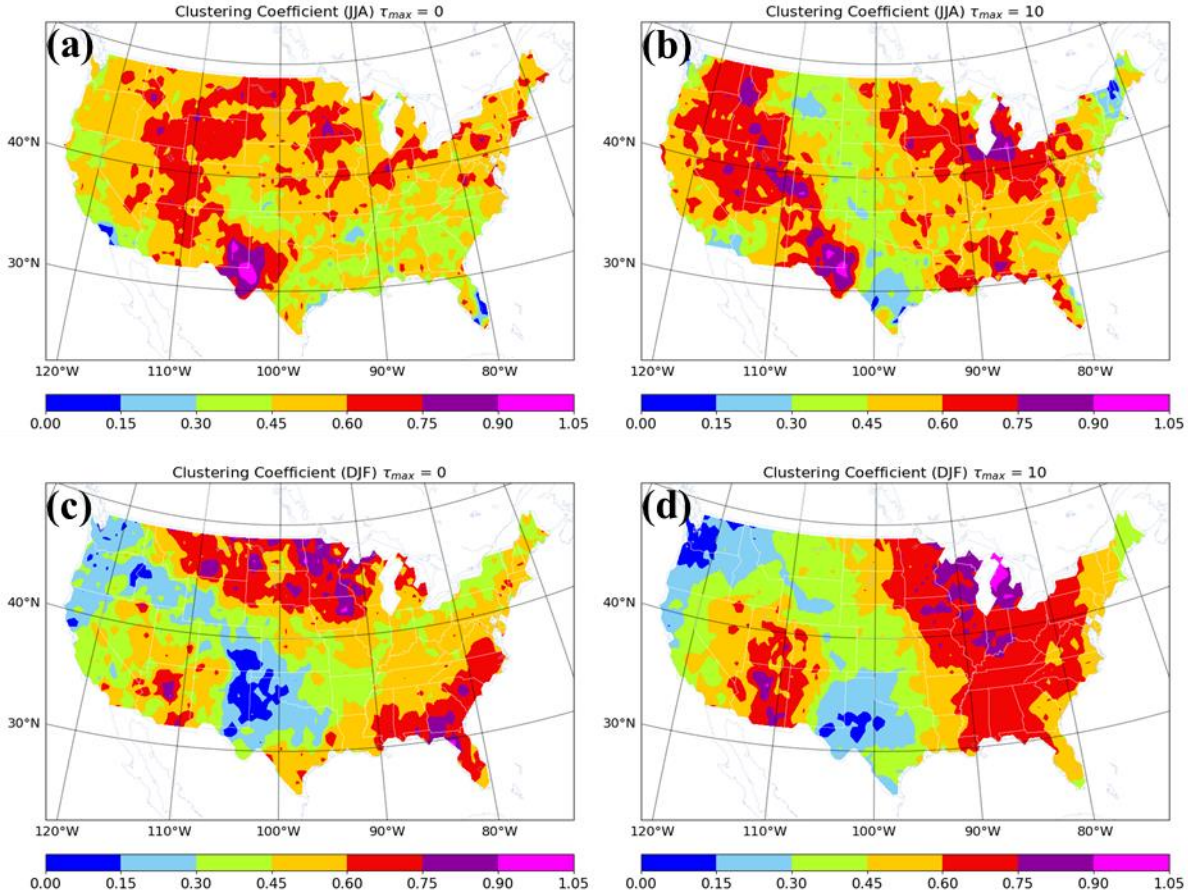


Figure 7. Normalized clustering coefficient, CC, for summer (a)-(b) and winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ and the right ones to $\tau_{max} = 10$ days.

- Betweenness centrality

The significance of a grid point within the global topology of the CN system is determined by the magnitude of the BC (Donges et al., 2009).

During the JJA season, large BC are noted in the coastal areas of the western regions notably, Pacific Northwest region of Western Washington, and Southwest of California extending to the southwest of Arizona at both $\tau_{max} = 0$ (Figure 8a) and $\tau_{max} = 10$ days (Figure

8b). Interestingly, heatwaves have been reported to propagate from the Southwest regions of California into many inland regions of the western USA, including California Central Valley, southern Nevada, and western Arizona (Lee and Grotjahn, 2016). Additionally, Mondal and Mishra (2021) noted southern California as one of the important regions where heatwaves occurring in large parts of the western USA originate from. Furthermore, regions of large BC could be observed in the coastal areas along the Gulf Coast in the southeast, particularly southeastern Texas and Louisiana. These regions are important in the propagation of ETEs further into the Midwest region and Great Plains.

There is a clear path of large BC values that extends from the northern Great Plains spreading through east of the Rocky Mountains to the south in Texas separating the western half of the CONUS from the eastern half at $\tau_{max} = 10$ days (Figure 8b). However, this path is not that obvious when $\tau_{max} = 0$ day (Figure 8a).

For the DJF season, largest BC can be observed over the Pacific Northwest and the Southern part (East of New Mexico and West of Texas) which extends to East of the Rocky Mountains in Colorado (Figures 8c and 8d). This suggests that these regions are crucial for the propagation of cold extremes (ETEs in Winter) over large spatial distance in the CONUS especially to the Great Plains, Midwest, and Central United States. At $\tau_{max} = 10$ days, large BC (greater than 0.3) spreads from the Pacific Northwest into the upper Great Plains (Figure 8d), however, this high value of BC does not extend to the upper Great Plains at $\tau_{max} = 0$ (Figure 8c). Furthermore, BC value greater than 0.3 extends from the south (Texas) to the northeast at $\tau_{max} = 0$, while such extension of BC value is not seen at $\tau_{max} = 10$. A clear pattern of large BC stretching from the Pacific Northwest into the upper Great Plains and further to the southern Plains in Texas is observed at τ_{max} greater than 0 (see Figure 20). The Northern Great Plains and

Upper Midwest are often affected by Arctic cold air masses that move southward, leading to significant drops in temperature and the development of cold waves (Grotjahn et al., 2016). The flat terrain and lack of significant topographic features might allow the cold air to spread more easily across the region.

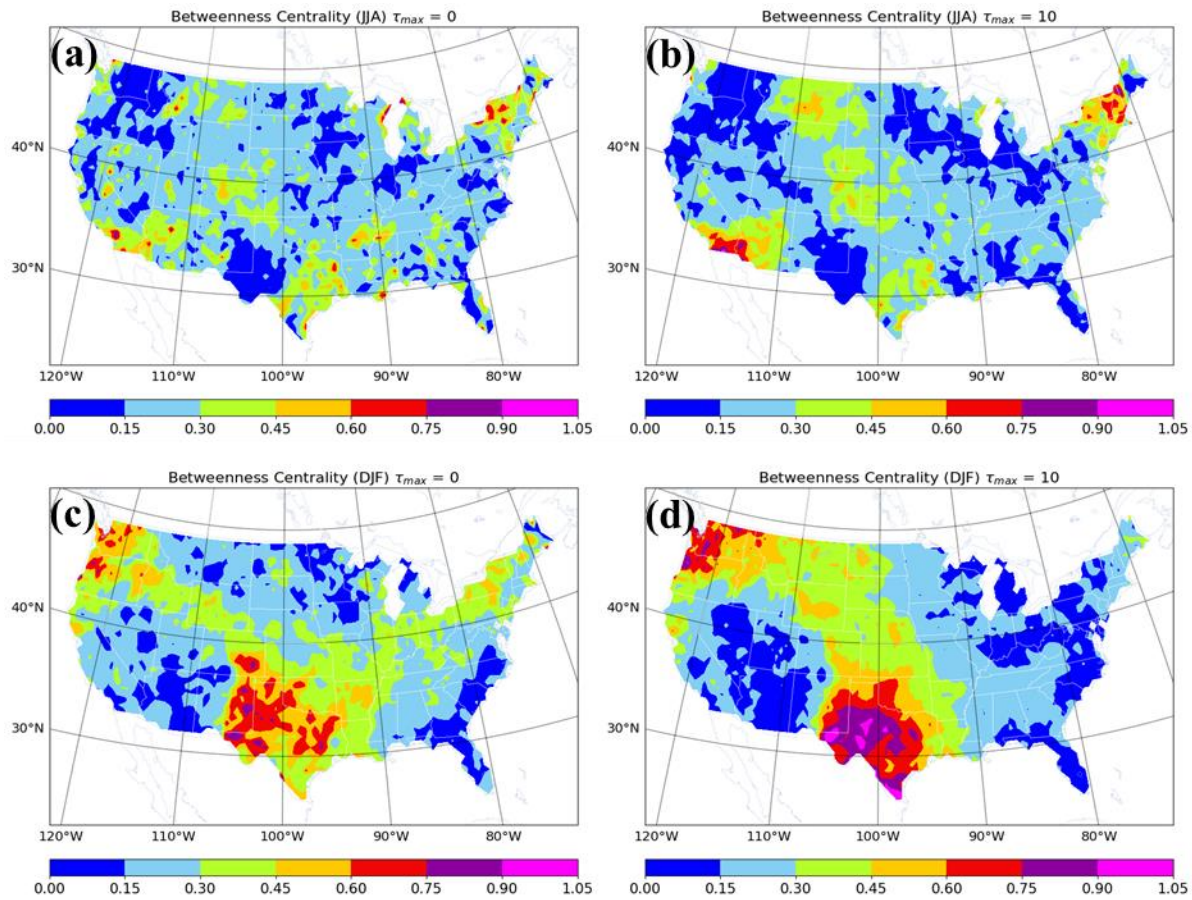


Figure 8. Normalized betweenness centrality, BC, for summer (a)-(b) and for winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days.

- Long-ranged directedness

The LD quantifies the characteristics of spatial distribution and geographic connectivity within the networks of ETEs. For the JJA season and $\tau_{max} = 0$ day, we observed large-LD regions mainly in southern California, south Florida, Arkansas, northeast and Lake Michigan (Figure 9a).

For $\tau_{max} = 10$ days, we found smaller LDs extended along the Rocky Mountains in the Mountain region of the CONUS, while larger LDs on the east of the Rocky Mountains stretched from the Northern Plains to the Gulf coast in Texas (Figure 9b). Interestingly, such patterns were not detected at 0-day lag time ($\tau_{max} = 0$ day). Mondal and Mishra (2021) also indicated that ETEs, such as heatwaves over the Rocky Mountains were highly localized and rarely propagated to farther distances. As can be seen in Figure 9b, the far Northeast displays the largest LD values followed by southern California, south Texas, Montana and northwest in the CONUS. As an example, the large LD values in south California are due to large MGDs (Figure 5b) and BCs (Figure 8b) as well as small CC values (Figure 7b) in this region. They also indicate long-range propagation potential of the ETEs, such as heatwaves, from this region farther into inland areas of western regions in the CONUS. Lee and Grotjahn (2016) also noted that this area played an important role in propagating heatwaves into many inland regions of the western USA, including the California Central Valley.

Large LDs (Figure 9b) with moderately large BCs (Figure 8b) observed near the Gulf coast and extended to the interior central U.S. indicate these regions are crucial for the transport of warm and humid air mass from the Gulf of Mexico into Midwest in summers. Summers in Midwest are often humid and warm due to a semi-permanent high-pressure system in the subtropical Atlantic that aid the inflow of humid and warm air masses from the Gulf of Mexico into this region (Washington, 2013).

For the DJF season, we observe a large LD at the Pacific Northwest. This extends through the Rockies to the southern parts of CONUS covering a broad region of Texas, part of New Mexico, Oklahoma, and the lower Great Plains at both $\tau_{max} = 0$ and $\tau_{max} = 10$ days (Figures 9c and 9d). In addition, we found a moderately large LD at the northeastern part of CONUS in New York, Pennsylvania including regions of the Appalachian Mountains. Small values of LD are observed in the west of the Rockies especially west of Colorado extending to regions Arizona, Utah and part of Idaho. During most winters, arctic air from Canada routinely plunges south into the central and eastern parts of CONUS. The blocking effect of the mountains and the moderating influence of the Pacific Ocean tend to moderate unusual cold in the far western US (Washington, 2013b). Note that large values of LD extend from the Pacific northwest into the Upper Great Plains when $\tau_{max} = 10$ days (Figure 9c), however, this is not the case at $\tau_{max} = 0$ day.

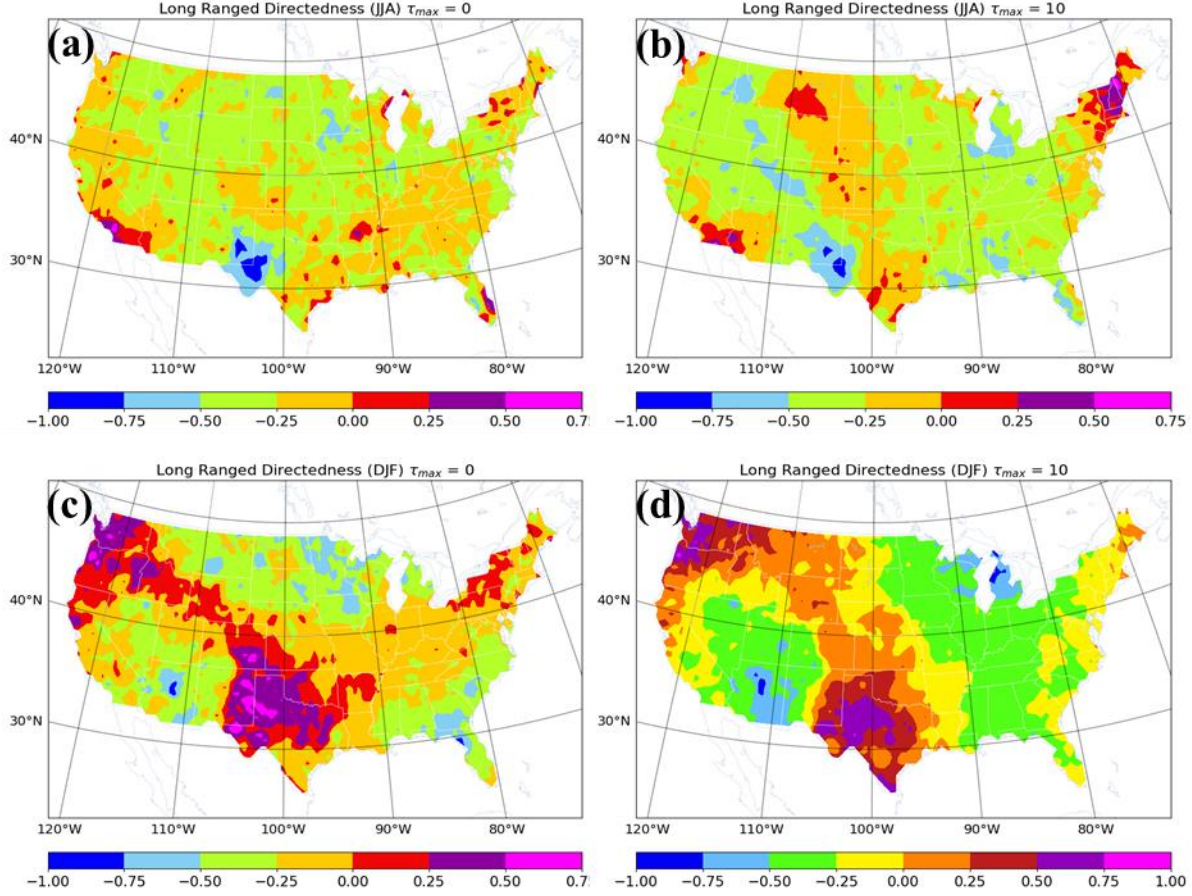


Figure 9. Long-ranged directedness, LD, for summer (a)-(b) and winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days.

Results of LD for different τ_{max} values ($= 0, 1, 3, 4, 5$ and 10) are presented in Figure 23 for the summer season and in Figure 24 for the winter season in the Appendix.

To gain further insight into the direction of propagation and synchronization of the ETes, we utilized another network measure known as directionality. This points to the direction along which synchronized extreme events occur (Boers et al., 2014). For a detailed explanation, check Boers et al. (2014) and Rheinwalt et al. (2016). For the JJA season, we observed the trajectory of the humid and warm air masses causing heat waves in the eastern regions of the US including the

Midwest propagating from the Gulf coast (Figure 10a). However, for the DJF season, we noted the transport route of the northerly arctic cold air masses into the Midwest and Northeast of the US (Figure 10b).

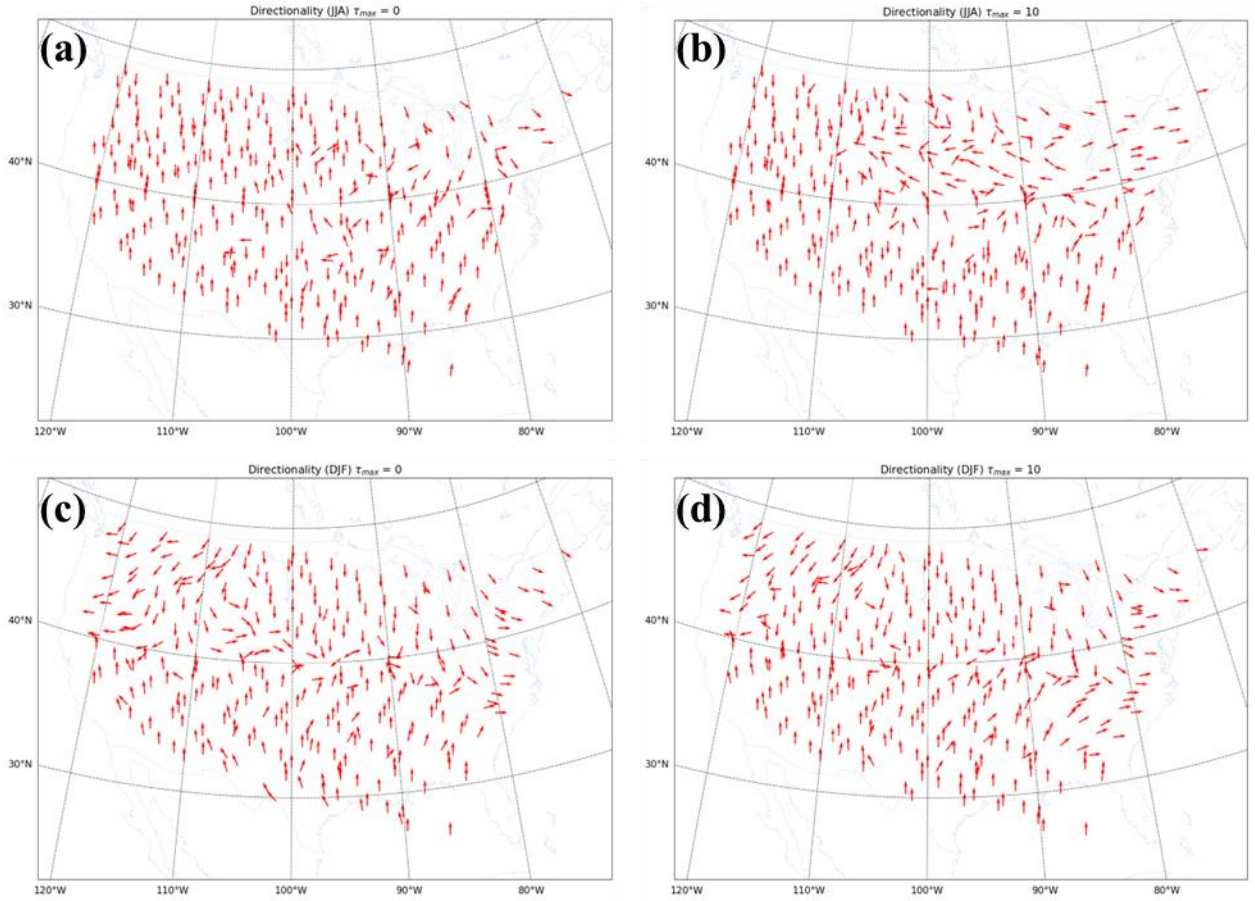


Figure 10. Directionality for summer (a)-(b) and for winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days.

4.4. Community detection analysis

Grid points (nodes) belonging to the same community exhibit greater synchronization with one another than those belonging to another community. We computed the modularity function using Equation 7 to identify distinct communities with the TN of the CONUS for both

JJA and DJF seasons using the Louvain method. We generated 100 distinct partitions through the Louvain method, each involving three iterations. Analyses were halted after the second iteration, as the identified communities remained unchanged thereafter. This procedure reduces noise and enhances robustness of the results obtained.

Figures 11a and 11b show the communities identified using different colors for the JJA and DJF seasons, respectively. We found four communities for the summer season, and three communities for the winter season. The fewer communities identified during winter compared to summer is consistent with Jamali et al. (2023). The authors applied complex network theory with event synchronization and time-warped edit distance techniques to analyze precipitation data over the CONUS and found lesser number of communities in winter than in summer. They reported that the smaller size of the communities in summer suggests a more regional atmospheric system in operation compared to winter.

The number of communities detected for the summer season (JJA) is consistent and similar with the result of Regonda et al. (2016). They found 4 communities for the regionalization of inter-annual variability in precipitation for the warm season (May through September) using the University of Delaware observation-based gridded precipitation data from 1982 to 2010 with a resolution of $0.5^\circ \times 0.5^\circ$. In another study, Vega et al. (1998) found five temperature regions using monthly temperature data obtained from the National Oceanic and Atmospheric Administration (NOAA) within the 344 climate divisions of the CONUS in the regionalization of the United States surface climate for the time frame 1895 to 1991. They applied the Rotated Principal Component Analysis to group climate divisions effectively into statistically homogeneous climate regions for both precipitation and temperature. Their temperature regions result (see their Figure 2) is similar to our winter communities result (Figure

10b). However, our result combines their PC1 (South) and PC3 (Northeast) into one community, and PC4 (Northwest) and PC5 (Southwest) into another community. Interestingly, there are high BC and low CC situated at the junction of the different communities detected (Figures 7 and 8), indicating that these communities interact with one another via exchange of air mass. The different communities detected here are further pointer to the presence of regional-scale weather patterns in the CONUS impacting various regions.

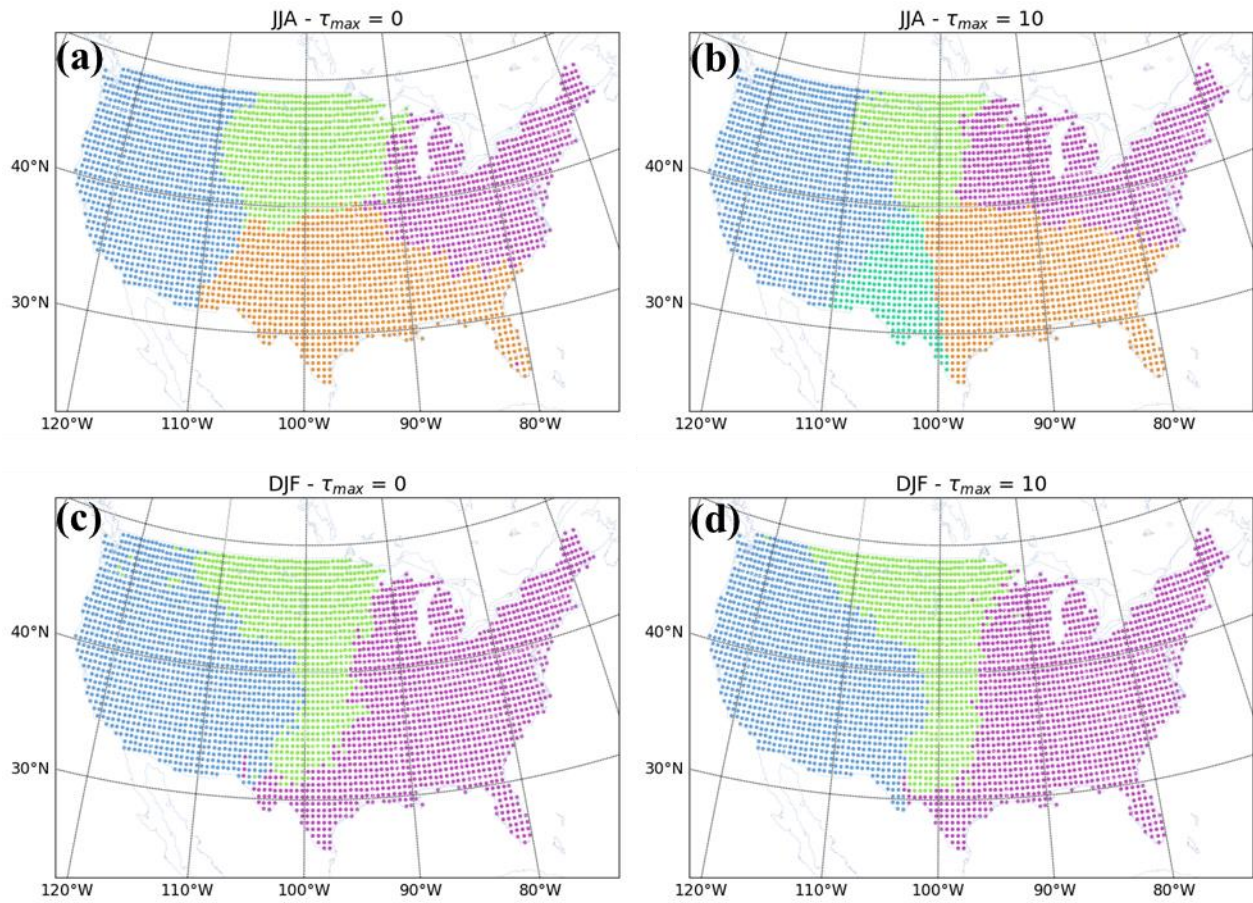


Figure 11. Communities detected within the network of ETEs for summer (a)-(b) and winter (c)-(d). The left plots represent results corresponding to $\tau_{max} = 0$ day and the right ones to $\tau_{max} = 10$ days.

4.5. Effect of τ_{max} on network measures

In this section, we discuss the influence/effect of multiscale lag time (τ_{max}) in the event synchronization (ES) approach on the patterns and propagation of extreme temperature events (ETEs) in the CONUS. In the ES method, τ_{max} defines the temporal delay between synchronous events, thereby impacting the structure of the resulting climate network.

At different τ_{max} , the degree centrality exhibits different ETEs patterns (Figures 15 and 16), suggesting that the number of grid-location displaying synchrony in occurrence of ETEs or nearly simultaneous ETEs occurrence with respect to a particular grid-location vary with the time lag or τ_{max} . From the results, we found that the Northeast region of the CONUS acts as hub (high DC value) of ETEs in both JJA and DJF regardless of the τ_{max} . Texas especially the southern region also acts as hub of ETEs during the winter (DJF) season (Figure 16). On the other hand, southern region of California serves as hub of ETEs in summer (JJA) at the different τ_{max} considered (Figure 15).

During the DJF season, with an increase in the τ_{max} , there is an increase in the long-range directedness (LD) starting from the Pacific northwest extending to the upper Great Plains, then over or across the Great Plains southward to Texas. This band of large LD (combination of large MGD, large BC, and small CC) (Figure 24) becomes more clearer as the τ_{max} value increases from 0 until it gets to 10 when the pattern starts to disappear. Similarly, during the JJA season, as τ_{max} increases there is a clear band of large LD (combination of large MGD, large BC, and small CC) (Figure 23) that extends over the Great Plains from north to south (sometimes extending to the Midwest). This pattern seems to start disappearing as τ_{max} gets to 10. From these results, the Great Plains and the Midwest are often under the influence of cold air masses as well as warm and humid air masses that result in extreme temperature events.

Chapter 5 - Conclusion

In this study, we applied the concept of complex network theory to investigate the spatiotemporal patterns and propagation of extreme temperature events (ETEs) in the contiguous United States for both summer and winter seasons. We defined ETEs in summer using the 95th percentile of the temperature distribution of grid points as a threshold, while in winter the threshold was set as the 5th percentile of the temperature distribution. To assess the similarity in the ETEs between any two grid points, we employed the event synchronization (ES) approach. We applied network metrics, including degree centrality (DC), mean geographic distance (MGD), betweenness centrality (BC), and clustering coefficients (CC). Additionally, we used a composite measure known as long-ranged directedness (LD) to characterize the spatial distribution and geographic connectivity of extreme temperature events.

Based on the degree centrality (DC), we identified hubs or hotspots, represented by grid points with numerous links, across the CONUS. Notable regions such as southern California, Lake Michigan areas, and the far Northeast exhibited hub characteristics in the summer, while hubs were identified in the Pacific Northwest, Texas, southern Florida, and the Northeast during the winter season. The mean geographic distance (MGD) network measure unveiled both local and regional connections, along with teleconnections within the CONUS. These findings were corroborated by results from clustering coefficients and betweenness centrality. Confirmation of teleconnections was achieved through the analysis of geographic distance distribution, revealing a crossover point around 3400 km for both seasons. This was further substantiated by results from the clustering coefficient and betweenness centrality. The teleconnection was confirmed by analyzing the geographic distance distribution. We found a crossover of 3400 km and 3600 km in summer, and 3400 km in winter for a regime shift from regional connection to teleconnection.

While at higher lag time the crossover for summer was found to be 3600 km, no crossover was discovered in winter.

From community detection analysis, the number of communities or clusters interacting through an exchange of air mass varied from summer to winter. Four communities were identified in summer while three communities were identified in winter, indicating systems of cold air mass causing ETEs in winter are larger in size compared to those of humid and warm air mass in summer. In all, there is greater synchronization of ETEs in winter than in summer. Findings from this study demonstrated that synchronization patterns of ETEs across different regions of the CONUS can help understand complex interactions and dependencies among different climatology and temperature extremes patterns.

Nonetheless, this study has few limitations. The data length can be a key limitation for complex network analysis of extreme events. Furthermore, high spatiotemporal resolution data will be needed to get more robust and detailed results.

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Appendix A - Geographic distance distribution

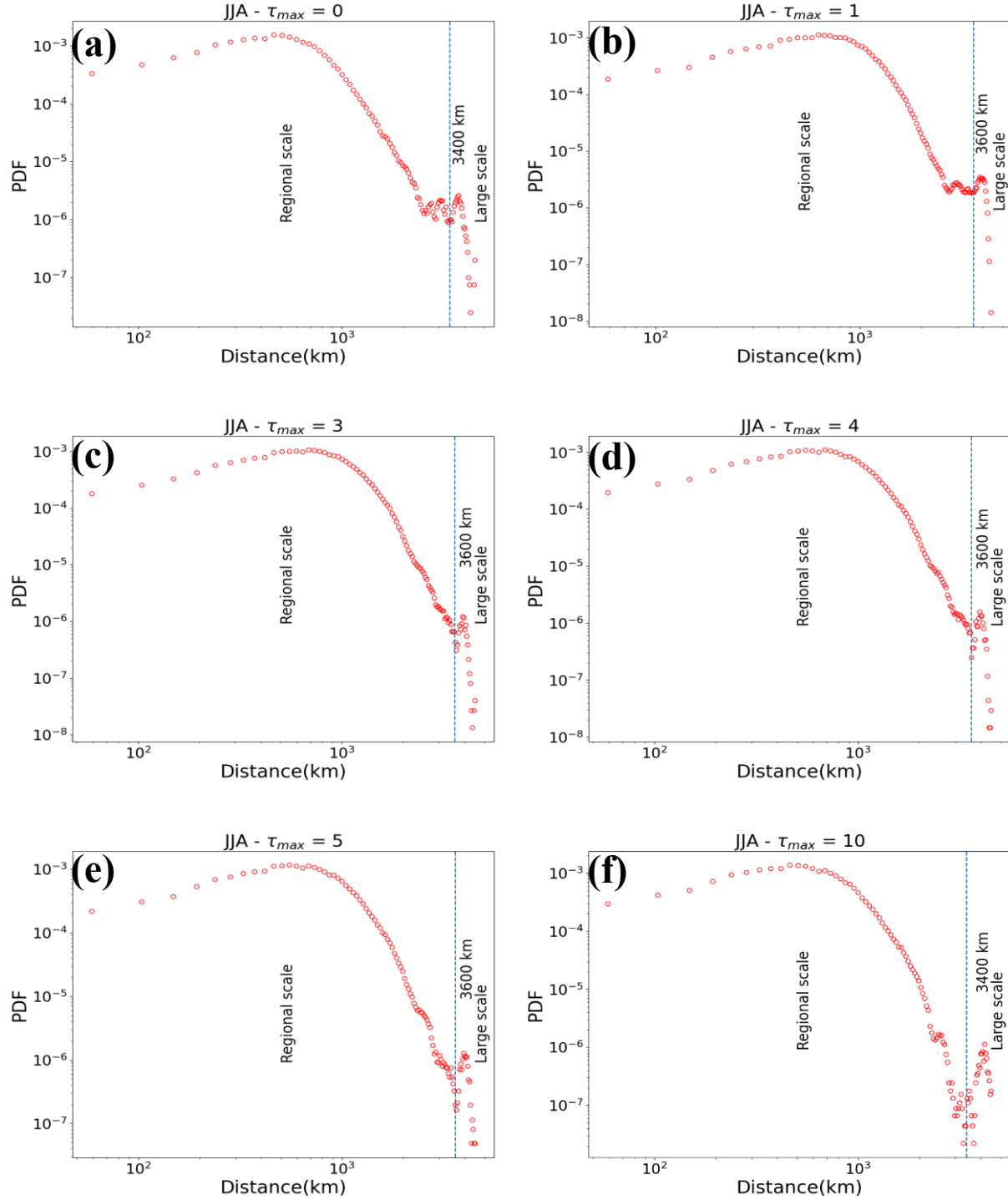


Figure 12. The geographic distance distribution of the connected grid points in the ETE network at different time lag (τ_{max}) for the summer season.

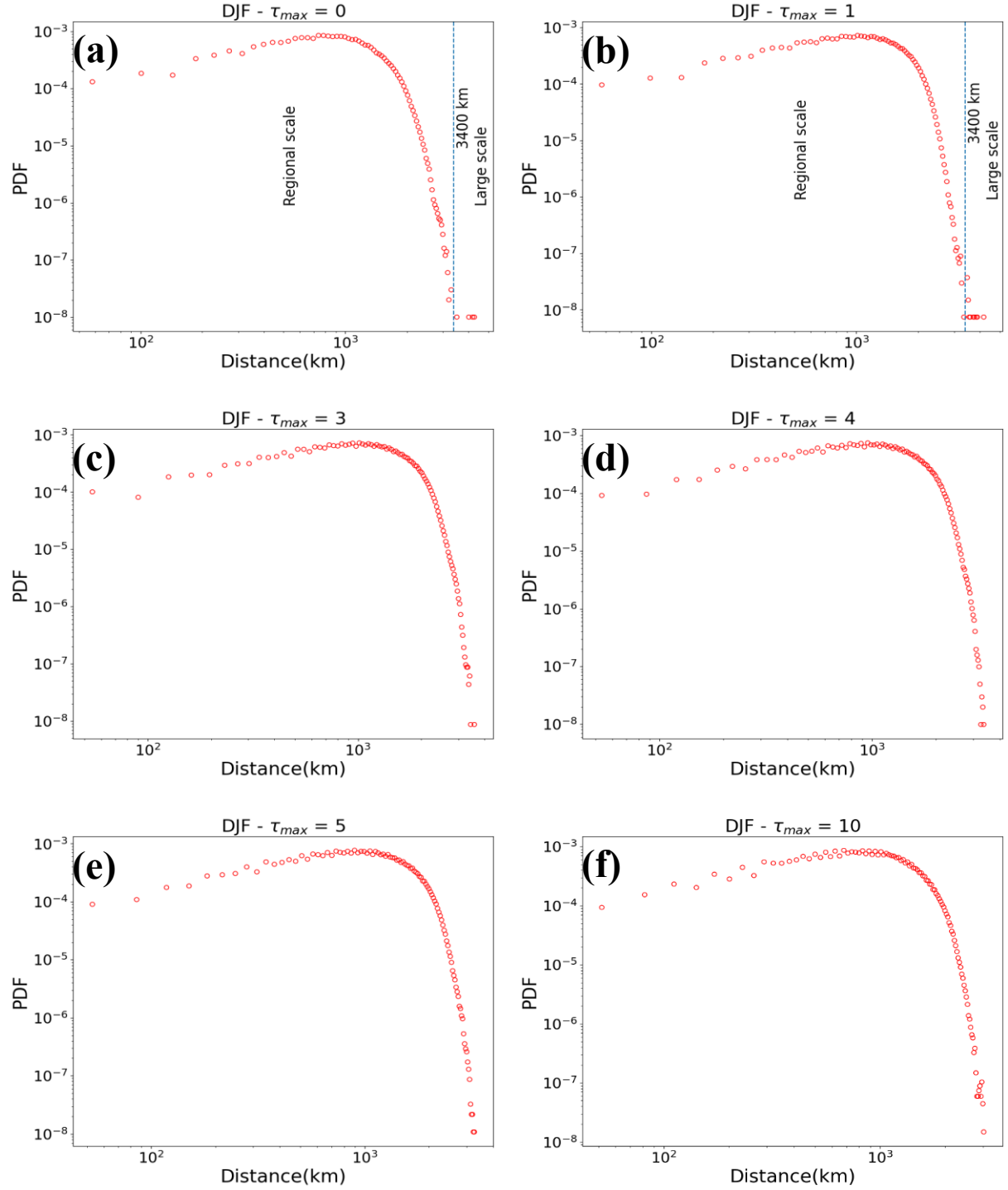


Figure 13. The geographic distance distribution of the connected grid points in the ETE network at different time lag (τ_{max}) for the winter season.

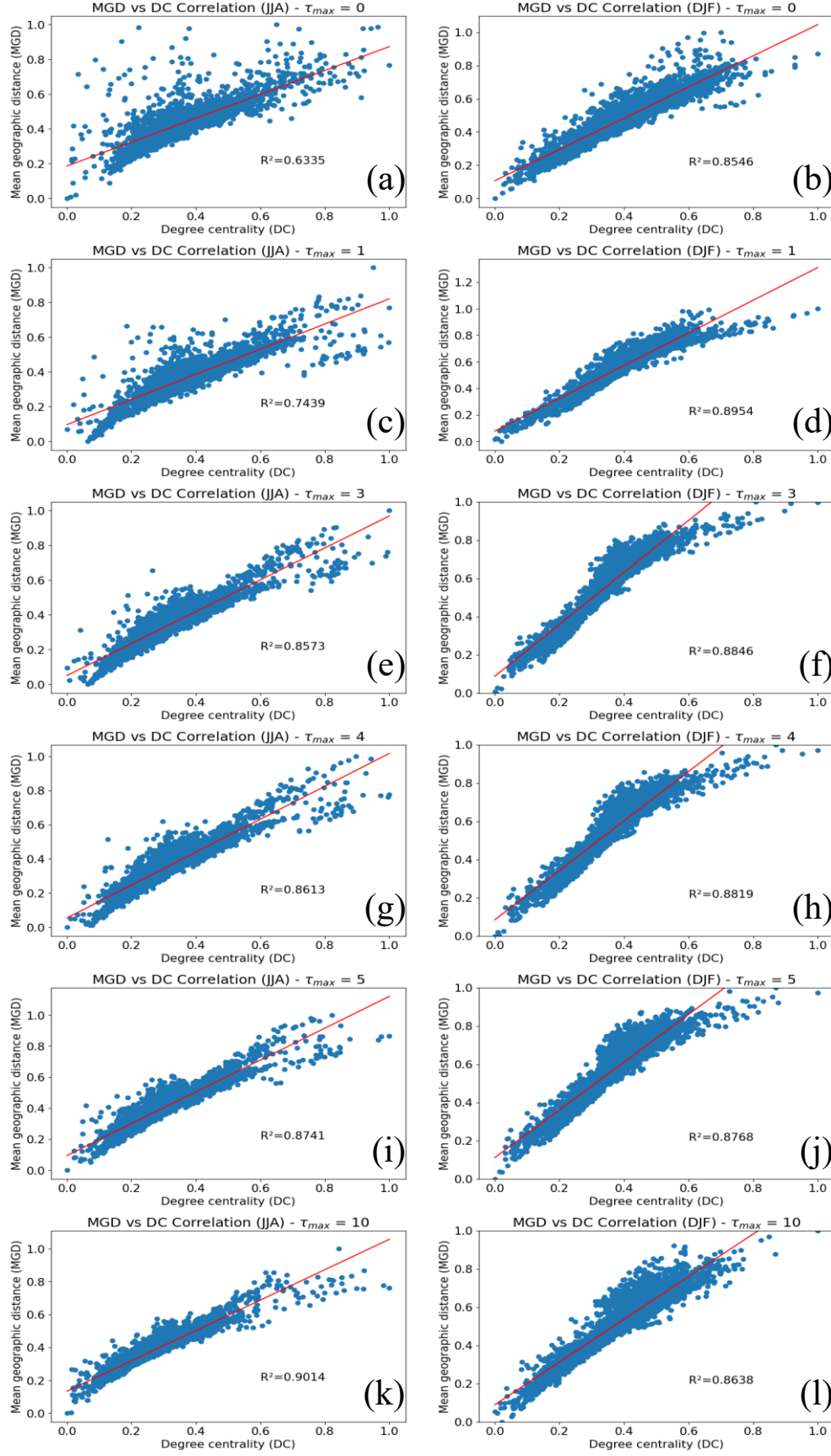


Figure 14. Scatterplot of the spatial correlation between mean geographic distance (MGD) and degree centrality (DC) over the CONUS.

Appendix B - Network measures

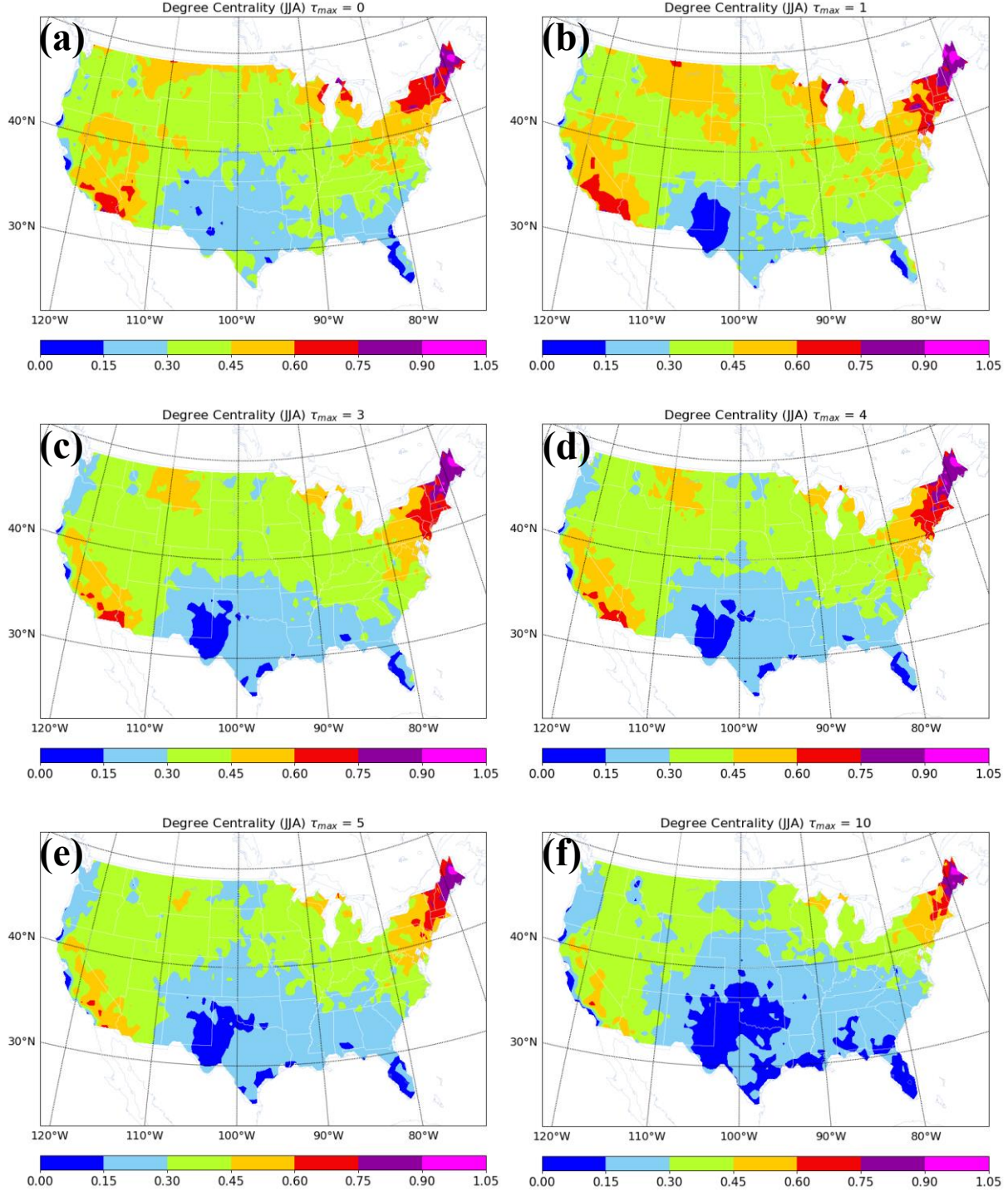


Figure 15. Normalized degree centrality (DC) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the summer season.

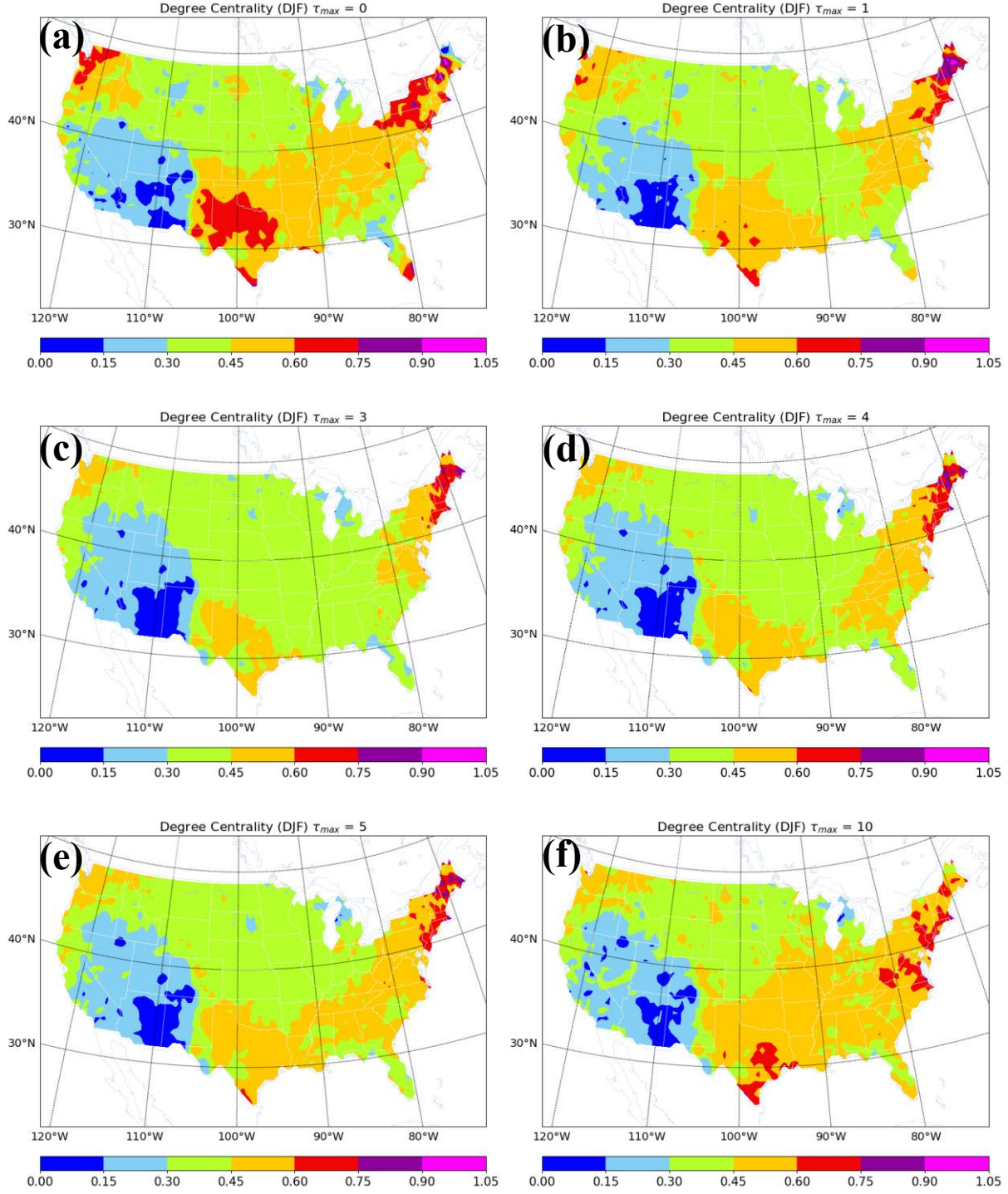


Figure 16. Normalized degree centrality (DC) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the winter season.

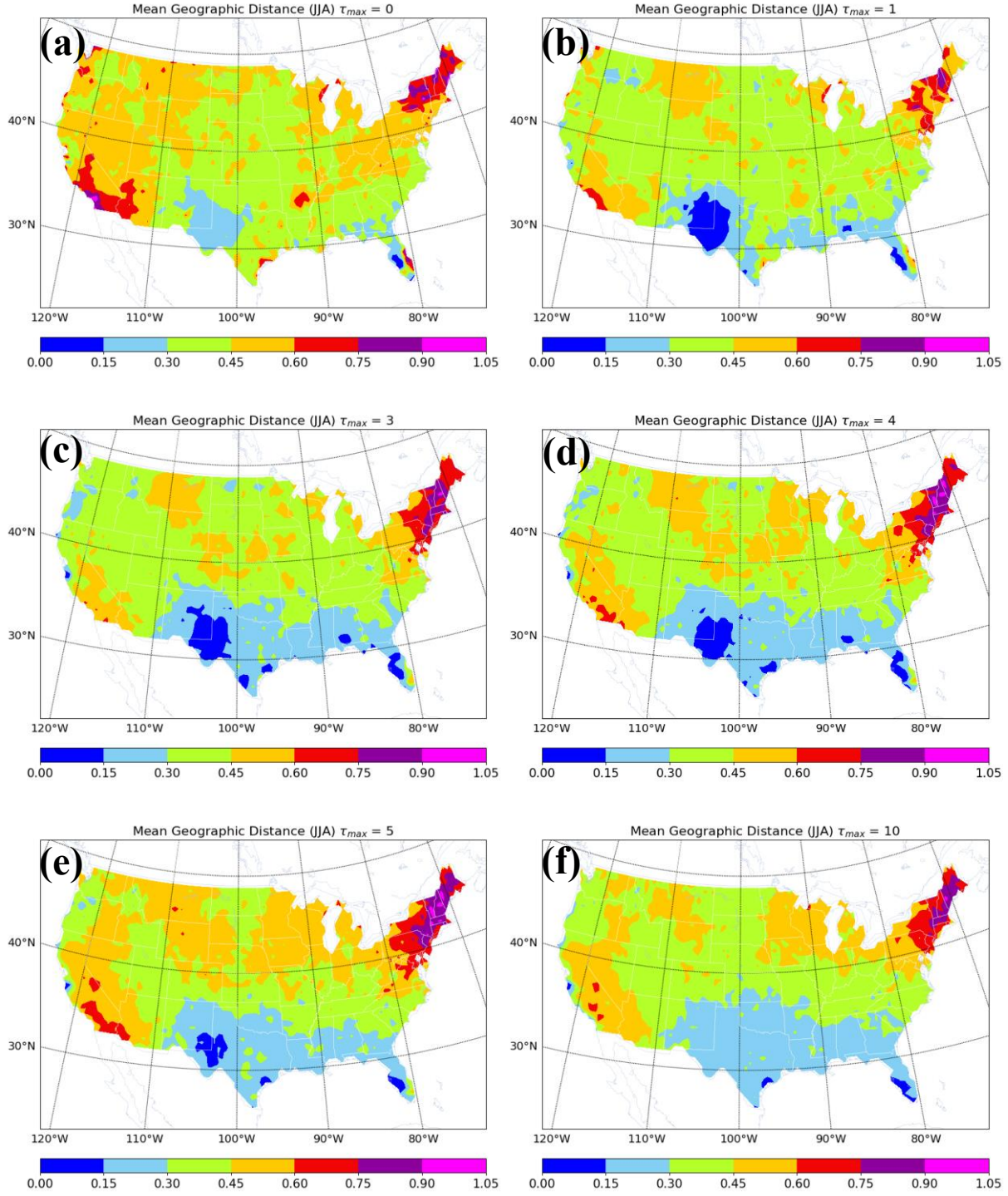


Figure 17. Normalized mean geographic distance (MGD) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the summer season.

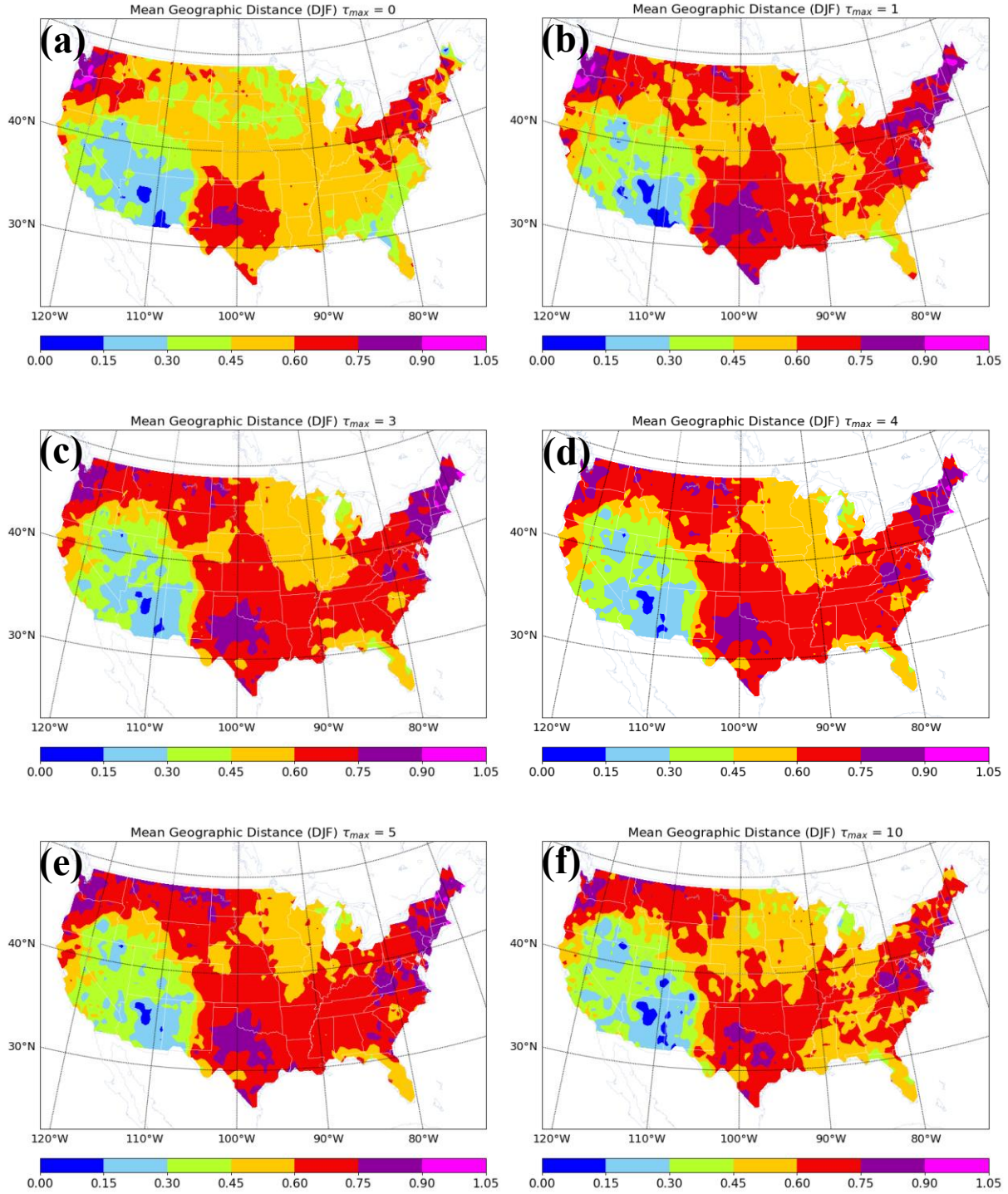


Figure 18. Normalized mean geographic distance (MGD) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the winter season.

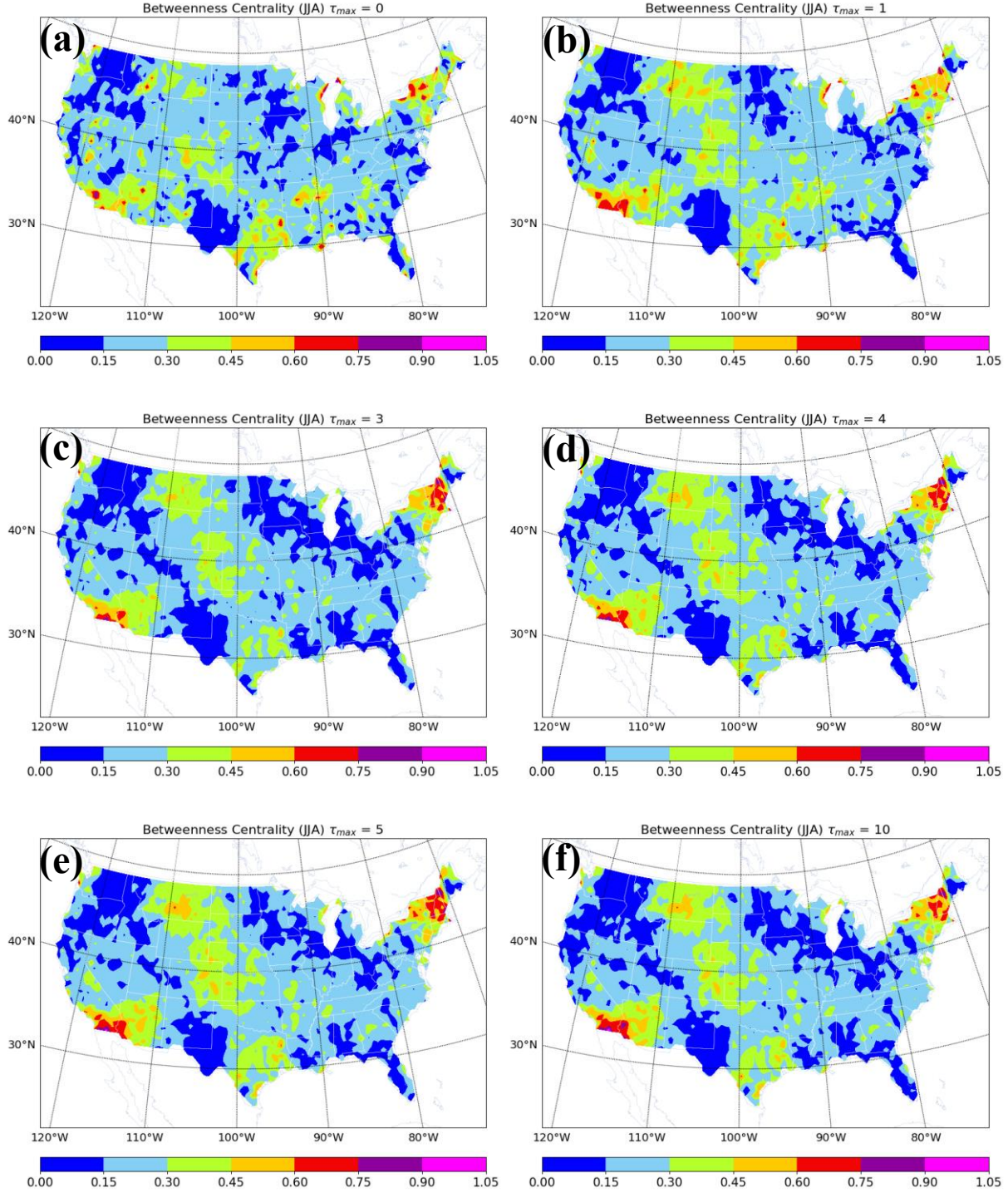


Figure 19. Normalized betweenness centrality (BC) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the summer season.

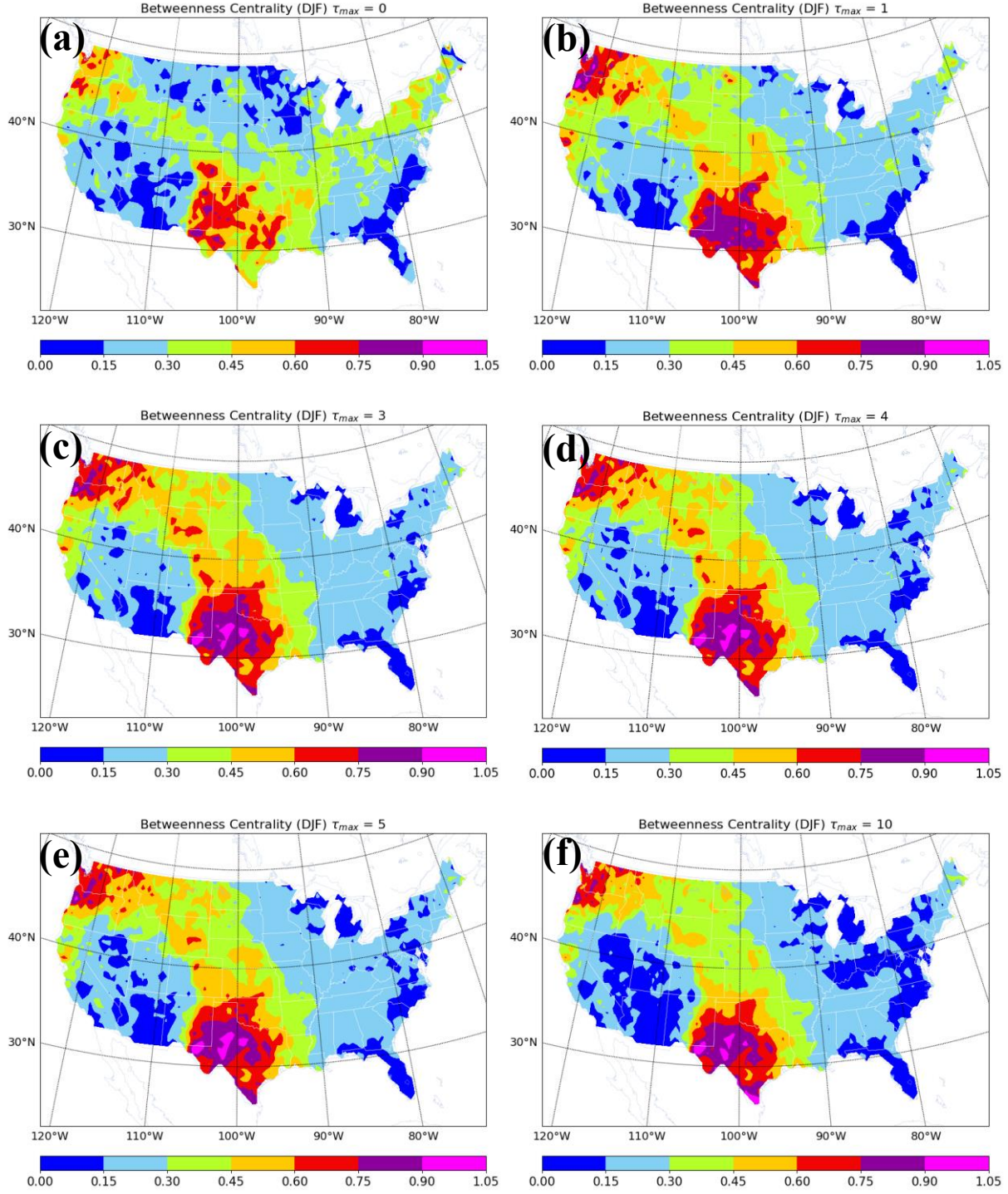


Figure 20. Normalized betweenness centrality (BC) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the winter season.

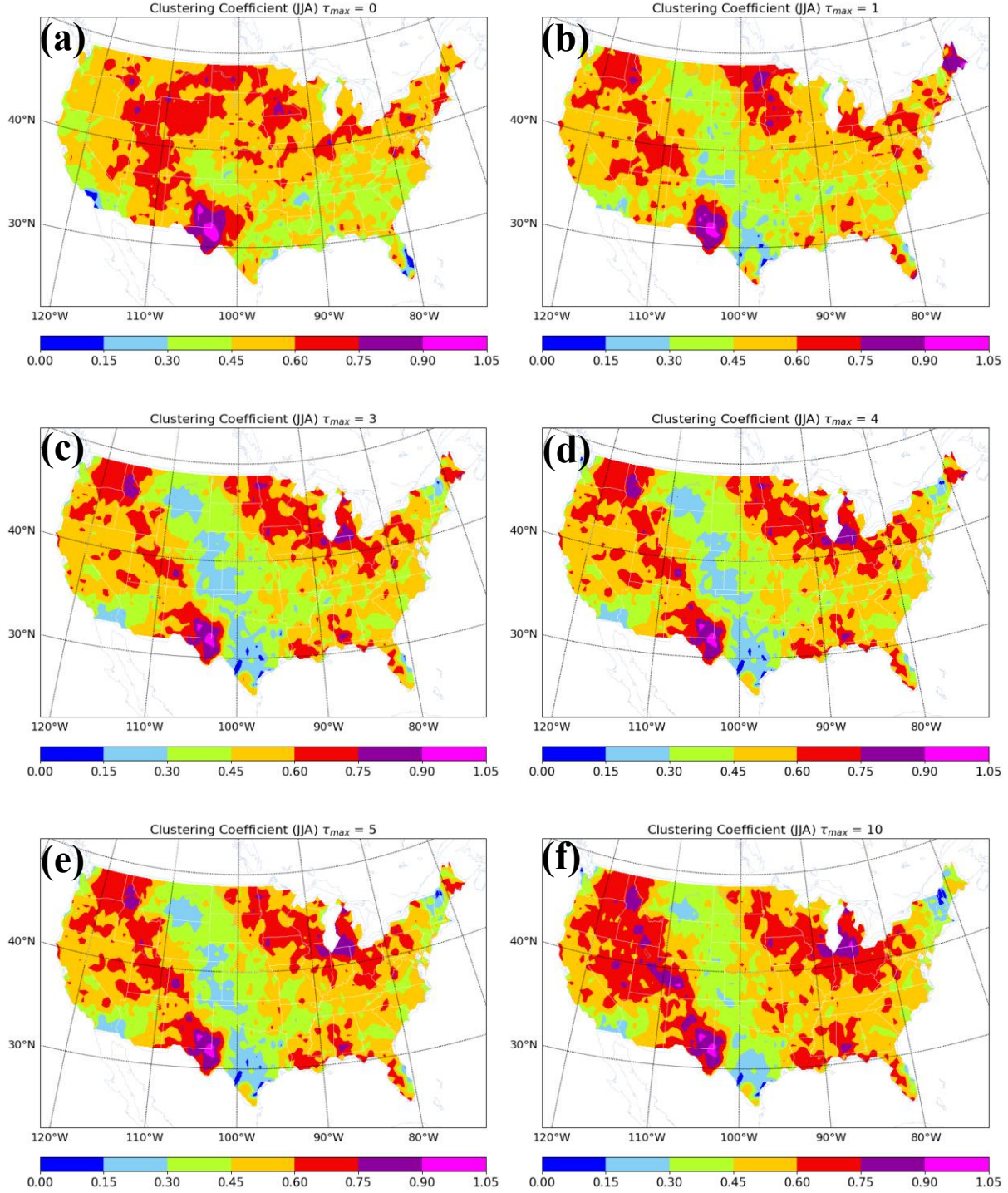


Figure 21. Normalized clustering coefficient (CC) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the summer season.

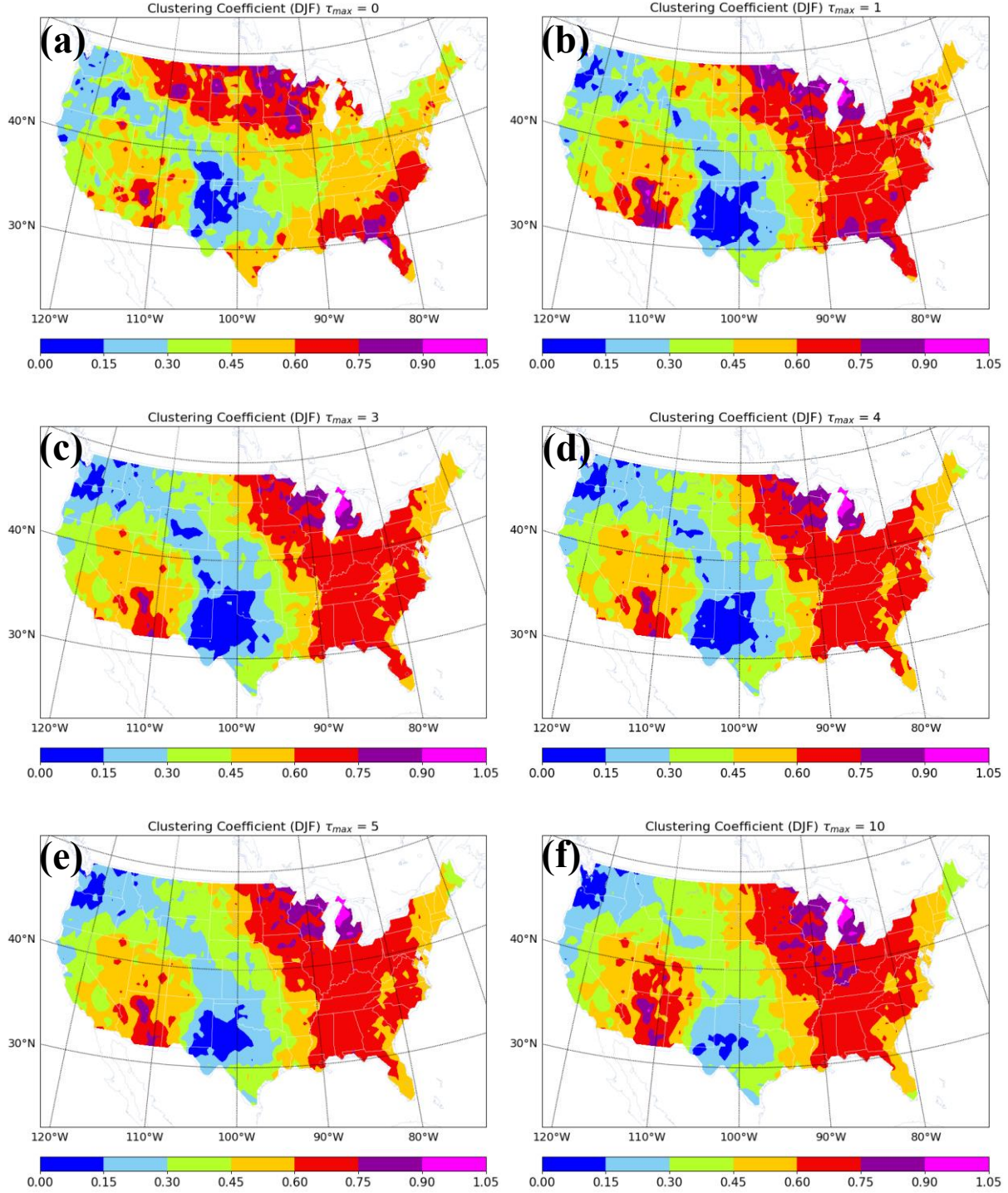


Figure 22. Normalized clustering coefficient (CC) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the winter season.

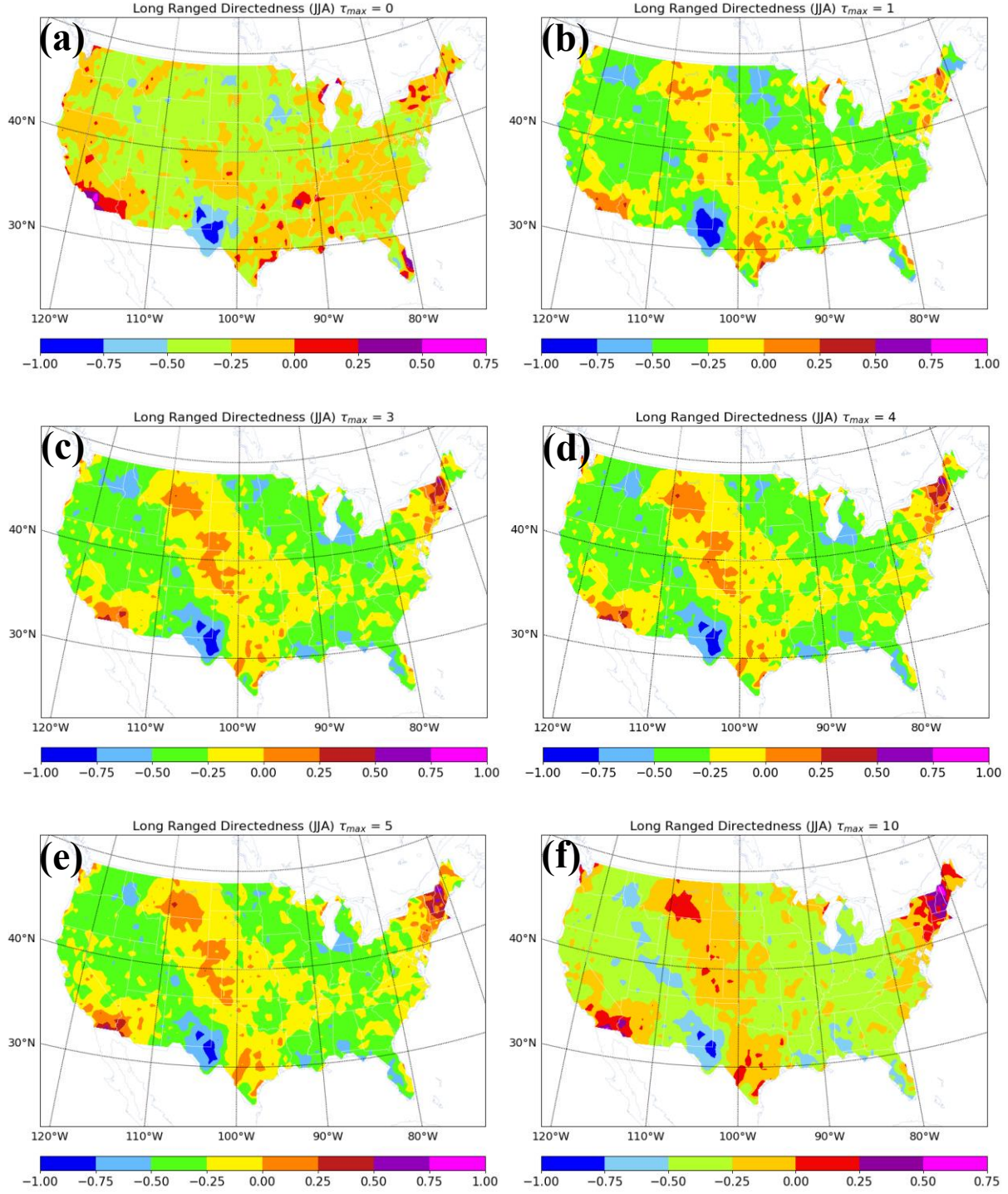


Figure 23. The long-ranged directedness (LD) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the summer season.

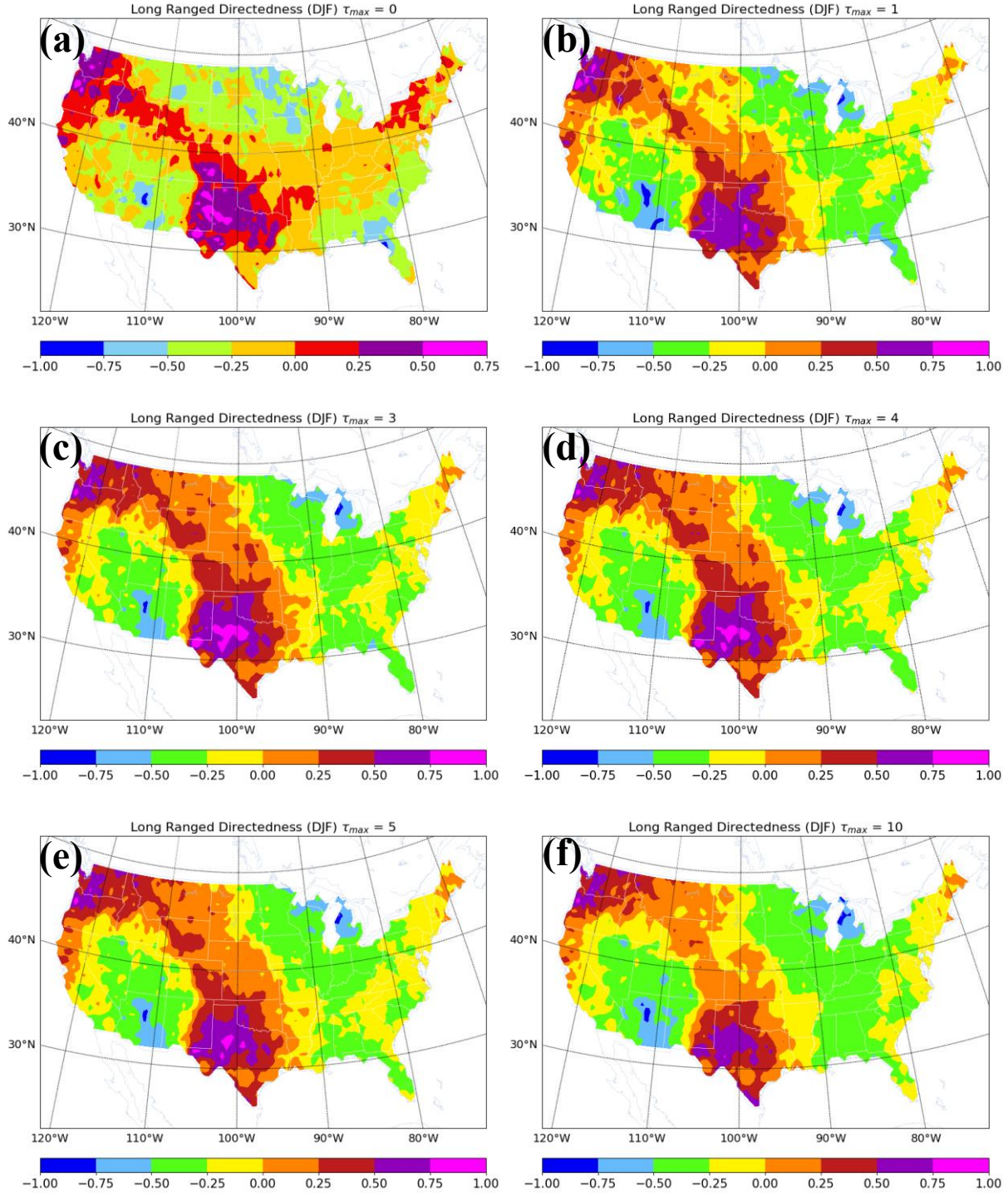


Figure 24. The long-ranged directedness (LD) at different τ_{max} (0, 1, 3, 4, 5 and 10) for the winter season.

Appendix C - Kolmogorov-Smirnov test

To check for similarity among the network measures obtained at the different τ_{max} , and to see if the network measures at two different τ_{max} are from the same distribution, the two-sample Kolmogorov-Smirnov test (KS-test) (Finner and Gontscharuk, 2018; Pratt and Gibbons, 1981) was carried out. The results of the p-values from the KS-test are shown in Tables 1 – 10 in this supporting information, with Tables 1 – 5 showing results for the JJA (summer) while Tables 6 – 10 showing results for the DJF (winter).

Table 1. P-values of statistical significance test (KS-test) for DC at different τ_{max} (JJA)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		2.73 $\times 10^{-26}$	4.22 $\times 10^{-23}$	2.45 $\times 10^{-22}$	8.03 $\times 10^{-81}$	6.93 $\times 10^{-180}$
$\tau_{max} = 1$			9.35 $\times 10^{-91}$	1.20 $\times 10^{-91}$	1.43 $\times 10^{-190}$	2.90 $\times 10^{-319}$
$\tau_{max} = 3$				8.88 $\times 10^{-2}$	2.92 $\times 10^{-38}$	5.11 $\times 10^{-139}$
$\tau_{max} = 4$					3.31 $\times 10^{-28}$	6.31 $\times 10^{-115}$
$\tau_{max} = 5$						3.88 $\times 10^{-40}$

Table 2. P-values of statistical significance test (KS-test) for MGD at different τ_{max} (JJA)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		1.48 $\times 10^{-97}$	1.97 $\times 10^{-124}$	1.50 $\times 10^{-62}$	1.34 $\times 10^{-27}$	4.50 $\times 10^{-72}$
$\tau_{max} = 1$			1.30 $\times 10^{-10}$	2.56 $\times 10^{-10}$	6.74 $\times 10^{-66}$	1.30 $\times 10^{-10}$
$\tau_{max} = 3$				5.82 $\times 10^{-16}$	1.80 $\times 10^{-75}$	3.24 $\times 10^{-12}$
$\tau_{max} = 4$					8.14 $\times 10^{-30}$	2.64 $\times 10^{-4}$
$\tau_{max} = 5$						2.43 $\times 10^{-31}$

Table 3. P-values of statistical significance test (KS-test) for BC at different τ_{max} (JJA)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		2.07 $\times 10^{-39}$	7.65 $\times 10^{-3}$	2.07 $\times 10^{-39}$	2.35 $\times 10^{-83}$	7.10 $\times 10^{-76}$
$\tau_{max} = 1$			2.73 $\times 10^{-26}$	3.90 $\times 10^{-1}$	2.77 $\times 10^{-11}$	5.47 $\times 10^{-9}$
$\tau_{max} = 3$				7.00 $\times 10^{-27}$	9.85 $\times 10^{-63}$	3.62 $\times 10^{-57}$
$\tau_{max} = 4$					2.13 $\times 10^{-9}$	6.61 $\times 10^{-7}$
$\tau_{max} = 5$						7.04 $\times 10^{-1}$

Table 4. P-values of statistical significance test (KS-test) for CC at different τ_{max} (JJA)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		3.88 $\times 10^{-320}$	1.06 $\times 10^{-39}$	5.89 $\times 10^{-31}$	8.78 $\times 10^{-31}$	1.10 $\times 10^{-10}$
$\tau_{max} = 1$			0.00	0.00	1.86 $\times 10^{-311}$	4.26 $\times 10^{-216}$
$\tau_{max} = 3$				4.34 $\times 10^{-2}$	2.49 $\times 10^{-3}$	7.00 $\times 10^{-23}$
$\tau_{max} = 4$					7.04 $\times 10^{-1}$	1.62 $\times 10^{-13}$
$\tau_{max} = 5$						7.82 $\times 10^{-11}$

Table 5. P-values of statistical significance test (KS-test) for LD at different τ_{max} (JJA)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		6.66 $\times 10^{-625}$	2.50 $\times 10^{-9}$	9.57 $\times 10^{-12}$	1.88 $\times 10^{-17}$	5.82 $\times 10^{-16}$
$\tau_{max} = 1$			1.25 $\times 10^{-203}$	4.04 $\times 10^{-209}$	4.29 $\times 10^{-252}$	1.85 $\times 10^{-154}$
$\tau_{max} = 3$				8.73 $\times 10^{-1}$	4.90 $\times 10^{-4}$	1.10 $\times 10^{-10}$
$\tau_{max} = 4$					6.48 $\times 10^{-3}$	6.11 $\times 10^{-13}$
$\tau_{max} = 5$						9.00 $\times 10^{-23}$

Table 6. P-values of statistical significance test (KS-test) for DC at different τ_{max} (DJF)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		3.74 $\times 10^{-15}$	3.99 $\times 10^{-98}$	2.58 $\times 10^{-41}$	2.50 $\times 10^{-28}$	1.73 $\times 10^{-4}$
$\tau_{max} = 1$			1.20 $\times 10^{-59}$	6.59 $\times 10^{-11}$	1.12 $\times 10^{-4}$	4.50 $\times 10^{-17}$
$\tau_{max} = 3$				8.45 $\times 10^{-22}$	7.16 $\times 10^{-41}$	3.61 $\times 10^{-124}$
$\tau_{max} = 4$					5.41 $\times 10^{-4}$	1.46 $\times 10^{-49}$
$\tau_{max} = 5$						3.31 $\times 10^{-28}$

Table 7. P-values of statistical significance test (KS-test) for MGD at different τ_{max} (DJF)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		8.94 $\times 10^{-146}$	1.43 $\times 10^{-173}$	6.05 $\times 10^{-173}$	1.61 $\times 10^{-227}$	3.12 $\times 10^{-102}$
$\tau_{max} = 1$			7.46 $\times 10^{-9}$	2.93 $\times 10^{-9}$	2.34 $\times 10^{-25}$	7.46 $\times 10^{-9}$
$\tau_{max} = 3$				7.04 $\times 10^{-1}$	5.55 $\times 10^{-11}$	1.79 $\times 10^{-25}$
$\tau_{max} = 4$					2.16 $\times 10^{-8}$	3.07 $\times 10^{-27}$
$\tau_{max} = 5$						2.12 $\times 10^{-54}$

Table 8. P-values of statistical significance test (KS-test) for BC at different τ_{max} (DJF)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		5.39 $\times 10^{-108}$	1.44 $\times 10^{-83}$	1.88 $\times 10^{-81}$	1.04 $\times 10^{-77}$	7.14 $\times 10^{-51}$
$\tau_{max} = 1$			8.65 $\times 10^{-7}$	4.01 $\times 10^{-9}$	8.00 $\times 10^{-12}$	7.60 $\times 10^{-40}$
$\tau_{max} = 3$				8.57 $\times 10^{-1}$	1.78 $\times 10^{-1}$	1.63 $\times 10^{-19}$
$\tau_{max} = 4$					7.85 $\times 10^{-1}$	4.71 $\times 10^{-16}$
$\tau_{max} = 5$						6.11 $\times 10^{-13}$

Table 9. P-values of statistical significance test (KS-test) for CC at different τ_{max} (DJF)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		1.22 $\times 10^{-20}$	1.55 $\times 10^{-12}$	3.02 $\times 10^{-10}$	3.92 $\times 10^{-11}$	3.98 $\times 10^{-18}$
$\tau_{max} = 1$			1.60 $\times 10^{-5}$	3.61 $\times 10^{-4}$	2.85 $\times 10^{-2}$	6.61 $\times 10^{-40}$
$\tau_{max} = 3$				6.00 $\times 10^{-1}$	9.78 $\times 10^{-3}$	4.59 $\times 10^{-15}$
$\tau_{max} = 4$					1.43 $\times 10^{-1}$	1.55 $\times 10^{-12}$
$\tau_{max} = 5$						1.13 $\times 10^{-6}$

Table 10. P-values of statistical significance test (KS-test) for LD at different τ_{max} (DJF)

	$\tau_{max} = 0$	$\tau_{max} = 1$	$\tau_{max} = 3$	$\tau_{max} = 4$	$\tau_{max} = 5$	$\tau_{max} = 10$
$\tau_{max} = 0$		1.26 $\times 10^{-14}$	1.44 $\times 10^{-36}$	3.00 $\times 10^{-32}$	8.14 $\times 10^{-30}$	1.44 $\times 10^{-7}$
$\tau_{max} = 1$			6.82 $\times 10^{-6}$	2.14 $\times 10^{-4}$	2.27 $\times 10^{-3}$	6.82 $\times 10^{-6}$
$\tau_{max} = 3$				9.03 $\times 10^{-1}$	2.97 $\times 10^{-1}$	1.55 $\times 10^{-12}$
$\tau_{max} = 4$					9.17 $\times 10^{-1}$	1.10 $\times 10^{-10}$
$\tau_{max} = 5$						1.95 $\times 10^{-11}$