Network-synchronization analysis reveals the weakening tropical circulations

Zijin Geng,1 Yongwen Zhang,2 Bo Lu,3 Jingfang Fan,1 Ziming Zhao,1 and Xiaosong Chen1

1School of Systems Science, Beijing Normal University, Beijing, China, 100875 2Data Science Research Center, Faculty of Science, Kunming University of Science and Technology, Kunming, Yunnan, China, 650500 3Laboratory for Climate Studies and CMA-NJU Joint Laboratory for Climate Prediction Studies, National Climate Center, China Meteorological Administration, Beijing, China,100081

Key Points:
• Showing global synchronization network patterns of extreme 500-hPa geopotential field
• Uncovering two synchronization networks associated with tropical circulations and Rossby waves respectively
• Demonstrating significant weakening synchronization patterns in the topics under climate change

Corresponding author: Yongwen Zhang, zhangyongwen77@gmail.com
Corresponding author: Xiaosong Chen, chenxs@bnu.edu.cn

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1029/2021GL093582.

This article is protected by copyright. All rights reserved.
Abstract
The impact of climate change on extreme weather is one of the most concerning problems. Climate change could cause more frequent and unexpected extreme weather. Still, synchronization features of extreme weather under climate change are not fully understood. Here, we develop a climate network approach to study global synchronization patterns of extreme events based on the 500-hPa geopotential field. We find that a positive event synchronization (PES) network is associated with the tropical circulations in the tropics; a negative event synchronization (NES) network is associated with the large-scale atmospheric Rossby waves in mid-latitudes. By studying temporal evolution of the PES network, we find that the synchronization strengths in the tropics are weakening under climate change in relation to the slowing down of tropical circulations. Furthermore, our results show that the strength of synchronization in Africa and the Atlantic Ocean decrease faster than other regions.

Plain Language Summary
Climate change could result in the changes of the large-scale atmospheric and oceanic circulations, which could change the correlations between different regions. Currently, understanding of synchronization features of extreme weather is very limited. During the last two decades, complex network theory has been demonstrated as a useful tool for studying real-world systems. Here, we perform a climate network-synchronization approach to study global synchronization patterns based on extreme events of 500-hpa geopotential height. Different features of extreme event synchronization can be detected by positive-synchronization and negative-synchronization networks. Furthermore, we investigate the impacts of climate change on the synchronization patterns from region to region in the tropics. All the regions show a weakening tendency with years, especially in Africa and the Atlantic Ocean. We associate this phenomenon to the weakening of tropical circulations.

1 Introduction
Climate change threatens our society in many perspective, e.g., human life, economy and natural resources which poses a significant challenge to humanity (Fan et al., 2018; Hsiang et al., 2011; Helbing, 2013; Schleussner et al., 2016; Carleton & Hsiang, 2016). In particular, global warming is the most visible sign of climate change. The Intergovernmental Panel on Climate Change (IPCC) has reported that surface temperatures are rising by about 0.2°C per decade (Pachauri et al., 2017). Global warming could change our ecosystem through influencing on climate variables such as surface temperature, sea level, precipitation, ocean currents and more (Alpert, 2004; Min et al., 2011; O’Gorman, 2014; Caesar et al., 2018).

Previous literatures (Pachauri et al., 2017; Tebaldi et al., 2006; Karl et al., 1995; Yonetani & Gordon, 2001) have raised the concern that the frequency and intensity of extreme weather could increase under ongoing climate change. Global temperature rising 2 °C above pre-industrial levels by time (Schellnhuber, n.d.; Knutson et al., 2018) could lead to a series of extreme weathers such as the intensity of precipitation (Tollefson, 2015), tropical cyclones (Chavas & Chen, 2020), more strong El Niño events (Ham, 2018), and extratropical storms (Meehl et al., 2000). Most recently, the water vapor from southern Indian Ocean and Arabian Sea was transported to India by two extreme monsoons, causing continuous heavy rainfall and the worst flooding during 2018 within recent 100 years (Mishra & Nagaraju, 2019); also an instability polar vortex over the Arctic went southward and intruded the United States, resulting in an extreme cold weather in 2019 (Xie et al., 2019); the Indian Ocean Dipole transferred the wet cold front to Africa, resulting a continuous dry in Australia, which was regarded as one of the main fuse of the forest fires lasting for more than 5 months (Phillips & Nogrady, 2020). Moreover, climate change and global warming could result in the changes of the large-scale atmospheric and oceanic circulations. The change of tropical circulation has become a central and hot issue (Ma et al., 2012; Betts & Ball, 1998; Knutson & Manabe, 1995; Quan et al., 2004). Some studies
(Fu, 2006) observed that the tropical circulation is slowing down with poleward expansion. However, others debated that the tropical circulation seems to have an intensive trend associating with the warming of the tropical ocean and the increasing frequency of the El Niño/Southern Oscillation (Tanaka et al., 2004).

During the last two decades, complex network theory has demonstrated its potential as a useful tool for exploring dynamical and structural properties of real-world systems from a wide variety of disciplines in physics, biology, and social science (Barabási & Albert, 1999; Newman, 2019; A. R. & L., 2002; C. R. & S., 2010; Brockmann & Helbing, 2013). It has been successfully applied for detecting and better understanding some features (Helbing et al., 2006) in complex systems (Pastor-Satorras et al., 2015; Morone & Makse, 2015; Gómez-Gardees et al., 2017). Climate system can be regarded as a highly coupled complex system (Ekhtiari et al., 2019). Recently, network approaches have also been implemented in climate sciences (Dijkstra et al., 2019; Fan et al., 2021). In climate systems, the geographical locations can be regarded as network nodes, and their interactions determined by the level of similarity (i.e., cross-correlation) are regarded as network links to construct climate networks. Climate network techniques have been successfully applied to improve our understanding of climate phenomena such as the El Niño/Southern Oscillation, the North Atlantic Oscillation, and Rossby waves (Donges et al., 2009; Fan et al., 2017; Guez et al., 2012; Tsonis & Swanson, 2008; Wang et al., 2013; Yamasaki et al., 2008; Agarwal et al., 2019). Furthermore, it has also been used to forecast extreme events (Boers et al., 2014; Ludescher et al., 2014, 2013; Meng et al., 2018) and provide a novel way to detect and evaluate the impacts of past and future climate change (Fan et al., 2018). In such cases, the method of Event Synchronization (ES) to measure the link of climate networks, developed in refs (Agarwal et al., 2017; Liang et al., 2015), is very useful, since it can deliver more robust results to study discrete data such as extreme rainfalls. ES has been successfully applied in many fields, e.g., brain network (Pfurtscheller & Da Silva, 1999; Krause et al., 1996), cardiovascular research (O’Connor et al., 2013), non-linear chaotic systems (Callahan et al., 1990) and climate sciences (Tass et al., 1998; Stolbova et al., 2014). A global extreme rainfall teleconnection pattern related to upper-level Rossby waves has been revealed by using the network-synchronization analysis (Boers et al., 2019).

Here, we perform a climate network-synchronization based approach to unveil global synchronization patterns based on the 500-hpa geopotential height data. This data can well describe the atmospheric circulations in the upper air. Different from the previous studies (Boers et al., 2019; Malik et al., 2012; Rheinwalt et al., 2016), here both the positive-synchronization (PES) and negative-synchronization (NES) networks are introduced. More features of extreme event synchronization can be detected by the two proposed networks. Furthermore, we investigate the impacts of global warming on the synchronization patterns of extreme geopotential heights from region to region in this study.

2 Materials and Methods

2.1 Data

We employ the daily 500-hpa geopotential height dataset from the global National Center for Environmental Prediction/National Center for Atmospheric Research (NCEP/NCAR) Reanalysis 1 data. This used data is with a spatial resolution, $2.5^\circ \times 2.5^\circ$, for the whole global, spanning from 1970 to 2019. To filter the trivial seasonal cycle and global warming tendency, we first detrend the original data by subtracting the mean seasonal cycle of the corresponding centered 10-year data. To test the robustness of our results for different dataset, we also employ the daily 500-hpa geopotential height data from the global ERA-Interim reanalysis with $0.25^\circ \times 0.25^\circ$ resolution from 1985 to 2019.
2.2 Extreme geopotential height event

Extreme geopotential height events are defined by three steps: (I) For each grid cell, the days with the absolute values of the detrended geopotential height above the 95 percentile of all days are identified as the extreme days; (II) the total extreme days can be divided into two types of extreme 'high' and 'low' days, where 'high' and 'low' represent that the detrended geopotential height are positive and negative respectively; (III) consecutive extreme days are considered as a single extreme event and placed on the centre of occurrence duration. Analogously, we can obtain the extreme 'high' and 'low' events.

2.3 Event synchronization

We denote the time series of the occurrence time (the centre of occurrence duration) of extreme geopotential height as \( \{t_{i,j}^x\}_{x=1,...,n}\) for grid cell \( i \), where \( n_i \) denotes the total number of extreme geopotential height at grid cell \( i \). The types of extreme geopotential height are represented as \( \{s_{i,j}^x\} \). If \( s_{i,j}^x = 1 \), the event \( x \) is an extreme 'high' event. If \( s_{i,j}^x = -1 \), this is an extreme 'low' event. We calculate the occurrence time interval between two events \( x \) and \( y \) from grids \( i \) and \( j \) respectively as \( d_{i,j}^{x,y} := t_{i,j}^{x,y} - t_{i,j}^{x,y} \). For the grids \( i \) and \( j \), the characteristic time interval can be defined as \( \tau_{i,j}^{x,y} := \min(t_{i,j}^{x+1,y} - t_{i,j}^{x,y}, t_{i,j}^{x,y} - t_{i,j}^{x-1,y}) / 2 \). We choose \( \tau_{\text{max}} = 10 \) days as maximum interval. If \( d_{i,j}^{x,y} < \tau_{i,j}^{x,y} \) and \( \tau_{i,j}^{x,y} \) we then consider that events \( x \) and \( y \) from grids \( i \) and \( j \) are a pair of synchronization events. Hence, the Event Synchronization (ES) between grids \( i \) and \( j \) (Quiroga et al., 2002) is defined by the summation of the number of synchronization pairs between them as follows:

\[
ES_{ij} := \|\{(x,y):|d_{i,j}^{x,y}| < \tau_{i,j}^{x,y} \wedge |d_{i,j}^{x,y}| \leq \tau_{\text{max}}\}\|,
\]

where \( |\cdot| \) denotes the absolute value, and \( \|\cdot\| \) denotes the cardinality of a set.

Due to take the 'high' and 'low' extreme geopotential height into consideration here, we can obtain the positive event synchronization \( +ES_{ij} \) (PES) and negative event synchronization \( -ES_{ij} \) (NES) as

\[
+ES_{ij} := \|\{(x,y):|d_{i,j}^{x,y}| < \tau_{i,j}^{x,y} \wedge |d_{i,j}^{x,y}| \leq \tau_{\text{max}} \wedge (s_{i,j}^x s_{i,j}^y = 1)\}\|,
-ES_{ij} := \|\{(x,y):|d_{i,j}^{x,y}| < \tau_{i,j}^{x,y} \wedge |d_{i,j}^{x,y}| \leq \tau_{\text{max}} \wedge (s_{i,j}^x s_{i,j}^y = -1)\}\|,
\]

To identify the direction of ES, we can consider the sign of \( d_{i,j}^{x,y} \). Thus, we define ES with the direction as:

\[
ES_{i\rightarrow j} := \|\{(x,y):-\tau_{i,j}^{x,y} < d_{i,j}^{x,y} \leq 0 \wedge |d_{i,j}^{x,y}| \leq \tau_{\text{max}}\}\|,
ES_{j\rightarrow i} := \|\{(x,y):0 \leq d_{i,j}^{x,y} < \tau_{i,j}^{x,y} \wedge |d_{i,j}^{x,y}| \leq \tau_{\text{max}}\}\|,
\]

where \( i\rightarrow j \) represents that the direction of ES is from \( i \) to \( j \), and vice versa. Similarly we can obtain \( +ES_{i\rightarrow j} \) \( +ES_{j\rightarrow i} \) for PES and NES respectively.

2.4 Synchronization networks

First, we introduce a threshold \( \Delta \) to identify the significant links. The threshold is estimated by the 99.5th percentile of the corresponding null-model ES distribution (Boers et al., 2010; Rheinwalt et al., 2016; Boers et al., 2016). Then, the adjacency matrix of ES network is defined as

\[
A_{ij} = \begin{cases} 1 - \delta_{ij}, & |ES_{ij}| > \Delta_{ij}, \\ 0, & |ES_{ij}| \leq \Delta_{ij}, \end{cases}
\]

where the Kronecker’s delta \( \delta_{ij} = 0 \) for \( i \neq j \) and \( \delta = 1 \) for \( i = j \). If \( A_{ij} = 1 \), there is a link between \( i \) and \( j \). If \( A_{ij} = 0 \), however, no link exists. To define a weighted network, for a
Figure 1. | Spatial and temporal distributions of extreme geopotential height events. Spatial distributions of a, total extreme geopotential height events and the fractions of b, 'high' extreme geopotential height events and c, 'low' extreme geopotential height events to total extreme geopotential height events. The temporal distributions of d, total extreme geopotential height events, e, 'high' extreme geopotential height events and f, 'low' extreme geopotential height events in months.

link between i and j we define its weight $W_{ij}$ as the ratio $\frac{|ES_{ij}|}{A_{ij}}$. Similarly, we can define the PES and NES networks.

The importance of grid cell $i$ in the ES network is usually characterized by its degree $k_i^{ES} = \sum_{j=1}^{N} A_{ij} \cos \theta_j$, where $\theta_j$ is the latitudes of the grid cell $i$ and $\cos \theta_j$ is proportional to the area size of grid $j$. More information can be taken into account by using a weighted degree $\tilde{k}_i^{ES} = \sum_{j=1}^{N} A_{ij} W_{ij} \cos \theta_j$. Due to the direction of ES, we can further introduce an out-weighted degree and an in-weighted degree as

$$\overline{\text{out} k_i^{ES}} = \sum_{j=1,d_{ij}^x < 0}^{N} A_{ij} W_{ij} \cos \theta_j,$$

$$\overline{\text{in} k_i^{ES}} = \sum_{j=1,d_{ij}^y > 0}^{N} A_{ij} W_{ij} \cos \theta_j,$$

(5)

where $\overline{\text{out} k_i^{ES}}$ ( $\overline{\text{in} k_i^{ES}}$ ) describes the total outgoing (incoming) synchronizations for grid $i$.

The direction from grid cell $i$ to $j$ is described by a unit vector $\vec{e}_{ij} = \frac{1}{l}(\delta \phi, \delta \theta)$, where $l = \sqrt{\delta \phi^2 + \delta \theta^2}$, $\delta \phi$ and $\delta \theta$ are the longitude and latitude differences between grids $i$ and $j$ respectively. We can define a weighted directional degree as

$$\tilde{k}_i^{ES} = \sum_{j=1,d_{ij}^x < 0}^{N} A_{ij} W_{ij} \cos \theta_j \vec{e}_{ij} + \sum_{j=1,d_{ij}^y > 0}^{N} A_{ij} W_{ij} \cos \theta_j (-\vec{e}_{ij}),$$

(6)

to describe the net influence direction for grid $i$ (Zhang et al., 2018). In the same way, we can obtain the weighted out- and in-degrees $\overline{\text{out} k_i^{ES}}$ ( $\overline{\text{in} k_i^{ES}}$ ) and $\overline{\text{in} k_i^{ES}}$ ( $\overline{\text{out} k_i^{ES}}$ ), and the weighted directional degree $\overline{\tilde{k}_i^{ES}}$ ( $\overline{\tilde{k}_i^{ES}}$ ) for the PES (NES) network.

3 Results

Firstly, we obtain total extreme geopotential height events over world between Jan. 2015 and Dec. 2019 (see Materials and Methods). Figure 1a shows the spatial distribution of total extreme geopotential height events. We observe that more extreme geopotential height events appear in the midlatitude (Subtropical High) regions than other regions for both the Southern Hemispheres (SH) and Northern Hemispheres (NH). This is consistent with previous study (Chang et al., 2002). Extreme geopotential height events are more frequent in subtropical highs, which resembles the distribution of storm track (Chang et al., 2002), e.g. Pacific and Atlantic Sectors of NH. We divide total extreme geopotential height events into 'high' and 'low' extreme geopotential height events as described in Materials and Methods. Figure 1b shows that the 'high' extreme geopotential height events are predominant around the equator. Conversely, the 'low' extreme geopotential height events are found to dominate in the midlatitude regions (15°N (S)–60°N (S)) as shown in Figure 1c. Nevertheless, the temporal distribution of extreme geopotential height events in months shows a similar behavior. All types of extreme geopotential height events favor winter in both SH and NH (see Figures 1d–f), since the geopotential height in winter has
more fluctuations associated with the synoptic of the upper air than other seasons (Lau & Nath, 1987).

Next, we calculate the positive event synchronization (PES) and negative event synchronization (NES) respectively according to Eq. (2). The network links (above the 99.5% confidence level of a control null-model) are identified. Different features of PES and NES networks are demonstrated by the probability density function (PDF) of the absolute values of occurrence time intervals $d_{i,j}^*$ and the PDF of geopotential distances $r$ as shown in Figure 2. The PDF of the occurrence time intervals for the PES network has a maximum at $d_{i,j}^* = 0$ then fast decays to near 0 after 5 days in Figure 2a. Whereas, for the NES network the PDF shows a much slower decay than that of the PES network in Figure 2a. The medium time intervals of PES network is within 1 days (red dashed line) and shorter than 2 days of NES network (blue dashed line) in Figure 2a. The PDF of the geographical distances for the PES network (Figure 2b) shows a peak around 1000 km (more than 10°). There is a peak at 3000 km (more than 30°) for the NES network in Figure 2b. Thus, the essential features of networks suggest that the NES network is associated with the larger scale atmospheric processes with the longer time delay than the PES network. The underlying mechanisms of the NES network could be related to the large-scale atmospheric Rossby waves whose half wavelength is around 3000 km (Wang et al., 2013; Zhang et al., 2019; C. E. K. M., 1999) as similar as the peak of the PDF of distances for the NES network. The power-law decay of distances $r^{-\alpha}$ from 800 to 10000 km with an exponent $\alpha = 1.4$ (Figure 2b) is found for the PES network which is associated with some climate and weather phenomena such as the tropical circulations and cyclones (Pierrehumbert R., 1986). The function below 800 km in Figure 2b is not satisfy with the power-law since the fraction of distances between all pairs of girds trivially increases as distance.

The importance of nodes in the ES network is characterized by the weighted degree (see Materials and Methods). Figures 3a–b show the maps of the weighted out-degrees and in-degrees calculated by Eq. (5), that describe the total outgoing and incoming synchronizations, respectively. The dominated out- and in-weighted degree patterns of the PES network are observed around the equator (30°S–30°N) in Figures 3a–b. Moreover, there are prominent in-degree basins in the equatorial West Pacific Ocean and the South-America (see Figure 3b). On the contrary, for the NES network, most of the large weighted in-degree and out-degrees are found in the midlatitude regions (30°N (S)–60°N (S)) in Figures 3c–d, that are associated with the active Rossby waves there. Besides, the net influence direction of synchronization is shown by the weighted directional degree, which is calculated by Eq. (6). In general, the directions are from east to west near the equator for the PNS network as shown in Figure 3e, which is consistent with the major direction of tropical circulations (G., 2014). In the midlatitude regions, the directions are from west to east for the NES network in Figure 3f as well as the Rossby waves (Wang et al., 2013; Zhang et al., 2019). Besides, we also check $\tau_{\text{max}} = 20$ and 30 days as maximum intervals. The results are similar to those of 10 days (see Fig. S1 and Fig. S2).

Due to the notable climate change in the tropics, it is thus interesting to study how the synchronization patterns of extreme geopotential height change under climate change in the tropics. Since we find that the tropics are dominated by the positive synchronization, in the following, we focus on the PES network. We separate 50 years (1970-2019) into 10 time windows and construct the PES network for each 5-years time window. We
Figure 4. Temporal evolution of degree patterns for the PES network for the tropics (30°S–30°N). Total a, weighted out-degree and b, weighted in-degree as functions of years. Green dashed lines represent linear fitted lines. The decreasing tendencies pass Mann-Kendall test (confident levels ≥90%).

Figure 5. Temporal evolution of degree patterns for the PES network for six regions. Total weighted out-degree as a function of years for a, Africa (AFR), b, the Indian Ocean (IO), c, the West Pacific Ocean (WPO), d, the Central Pacific Ocean (CPO), e, the East Pacific Ocean (EPO) and f, the Atlantic Ocean (AO). g-I Same as a-f but the total weighted in-degree. Green dashed lines represent linear fitted lines. Linear correlation coefficients (r-values) are given in the panels. Mann-Kendall tendency test of total weighted out-degree show confident levels of IO (<90%), WPO (<90%), CPO (<90%), EPO (>90%), AO (>90%) and AFR (>90%). For in-degree, confident levels of IO (<90%), WPO (<90%), CPO (<90%), AFR (>90%), EPO (>95%) and AO (>95%).

first calculated the total weighted out- (in-) degree for the entire tropics for the PES networks as a function of time as shown in Figure 4. Both out-degree and in-degree show a decreasing tendency with years and pass the Mann-Kendall test (H. B. M., 1945) at 90% confident level. The strength of atmospheric circulations in different regions in the tropics could decrease with different rates as mentioned in ref (Yu & Zwiers, 2010). Thus, we divide the tropics into six regions as shown in Figure 3a, including Africa (AFR), the Indian Ocean (IO), the West Pacific Ocean (WPO), the Central Pacific Ocean (CPO), the East Pacific Ocean (EPO) and the Atlantic Ocean (AO). Figure 5 shows the total weighted out- (in-) degree as a function of years for the six regions. All of them show a decreasing tendency with years for both the out- and in-degree (see Figure 5), among which AFR, EPO and AO pass the Mann-Kendall tendency test at high confident levels (>90%) such that decreasing tendencies are significant for them. However, for IO, WPO and CPO the confident levels are less than 90%. Indeed, the results show different decreasing rates for the six regions. These results could be attributed to the slow down of tropical circulations (Fan et al., 2018; Fu, 2006; Lu et al., 2007). Due to global warming, a large reduction in the meridional temperature gradient across the subtropics could lead to the reduction of the strength of tropical circulations (Seo et al., 2014).

Furthermore, we find that the rates of decay are different for different regions. The rates of decay in AFR and AO are faster than other regions for both the out- and in-degree. For WPO, the rate of decay of out-degree is faster than that of in-degree. To quantify such difference, we define a network divergence as the difference between out- and in-degree (i.e., $outk_{ES}^i - ink_{ES}^i$) as shown in Figure S3. For WPO, the divergence significantly switches from positive to negative with years in Figure S1d. This indicates that WPO becomes more vulnerable with more incoming links than outgoing links. We also test our results for the ERA-Interim reanalysis dataset between 1985–2019 as shown in Figures S4–S8. In general, the results are quite similar and robust for different datasets.

4 Conclusions

In summary, we have proposed a climate network-synchronization approach to study global extreme 500-hPa geopotential height. We find that there are two synchronization networks (PES and NES) with different characteristics. The PES network is dominant in the tropics and shows the distance distribution with power-law decay. For the NES network, the important nodes are located in the midlatitude regions. The time delay distribution of the NES network indicates a much slower and longer decay in comparison to that of the PES network. Moreover, there exists a peak around 3000 km for the distance distribution of the NES network that is corresponding to the half wave-length of Rossby.
waves. Thus, we infer that the PES and NES networks are associated with the tropical
circulations and the large-scale atmospheric Rossby waves respectively. According to the
directional degree distribution, we further demonstrate that the net directions of the PES
and NES networks are generally consistent with the directions of the tropical circulations
and the Rossby waves respectively.

To study the effects of the global warming in the tropics, we show the temporal
evolution of degree patterns for the PES network. We find that the synchronizations of ex-
treme geopotential height events between different areas in the tropics are weakening with
years. This phenomenon could be due to the weakening of the tropical circulation, which
is still controversial in previous studies (Fan et al., 2018; Fu, 2006; Lu et al., 2007; Seo et
al., 2014; Held & Soden, 2006; M. C. M., 2005). Our results could support the conclusion
that the tropical circulation is weakening under global change (Vecchi & Soden, 2007;
Kjellsson, 2014). Furthermore, the introduced network-based approach can be applied to
study other climate phenomena, especially other extreme climate events, in responding to
the global warming. Our methods may be also relevant for other fields like in the studies
of air pollution and earthquakes (Zhang et al., 2019, 2020).

Acknowledgments
We acknowledge the Key Research Program of Frontier Sciences, Chinese Academy of
Sciences (Grant No. QYZD-SSW-SYS019) for financial support. The data/reanalysis that
support the findings of this study are publicly available online: NCEP/NCAR Reanalysis
(https://psl.noaa.gov/data/gridded/data.ncep.reanalysis.html) and ERA5 Reanalysis
(https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5).

References
Agarwal, A., Caesar, L., Marwan, N., Maheswaran, R., & Kurths, J. (2019).
Network-based identification and characterization of teleconnections on dif-
ferent scales. Scientific Reports, 9, 1-12.
Agarwal, A., Marwan, N., Rathinasamy, M., Merz, B., & Kurths, J. (2017).
Multi-scale event synchronization analysis for unravelling climate processes:
a wavelet-based approach. Nonlinear. Proc. Geoph., 24(4), 599-611.
Alpert, P. (2004). The water crisis in the e. mediterranean—and relation to global
warming? In Water in the middle east and in north africa (p. 55-61). Springer,
New York.
Barabási, A. L., & Albert, R. (1999). Emergence of scaling in random networks.
Science, 286, 509-512.
Betts, A. K., & Ball, J. H. (1998). Fife surface climate and site-average dataset
1987–89. J. Atmos. Sci., 55(7), 1091-1108.
Boers, N., Bookhagen, B., Barbosa, H. M. J., Marwan, N., Kurths, J., & Marengo,
J. A. (2014). Prediction of extreme floods in the eastern central andes based
on a complex networks approach. Nat. Commun., 5, 5199.
Boers, N., Bookhagen, B., Marwan, N., & Kurths, J. (2016). Spatiotemporal charac-
teristics and synchronization of extreme rainfall in south america with focus on
the andes mountain range. Clim. Dynam., 46(1-2), 601-617.
Boers, N., Goswami, B., Rheinwalt, A., Bookhagen, B., Hoskins, B., & Kurths, J.
(2019). Complex networks reveal global pattern of extreme-rainfall teleconnec-
tions. Nature, 566, 373–377.
Brockmann, D., & Helbing, D. (2013). The hidden geometry of complex, network-
driven contagion phenomena. Science, 342(6164), 1337-1342.
Caesar, L., Rahmstorf, S., Robinson, A., Feulner, G., & Saba, V. (2018). Observed
fingerprint of a weakening atlantic ocean overturning circulation. Nature, 556,
191-196.
Callahan, D., Kennedy, K., & Subhlok, J. (1990). Analysis of event synchronization
in a parallel programming tool. ACM SIGPLAN Notices, 21-30.
Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science, 353*(6304), 1112-1112.
Chang, E. K. M., Lee, S., & Swanson, K. L. (2002). Storm track dynamics. *J. Clim., 15*(16), 2163-2183.
Chavas, D., & Chen, J. (2020). Tropical cyclones could last longer after landfall in a warming world. *Nature, 587*, 200-201.
Dijkstra, H. A., Emilio, H.-G., Masoller, C., & Barreiro, M. (2019). *Networks in climate*. Cambridge University Press.
Donges, J. F., Zou, Y., Marwan, N., & Kurths, J. (2009). The backbone of the climate network. *EPL, 87*(4).
Ekhtiari, N., Agarwal, A., Marwan, N., & Donner, R. V. (2019). Disentangling the multi-scale effects of sea-surface temperatures on global precipitation: A coupled networks approach. *Chaos, 29*(6), 063116.
Fan, J., Meng, J., Ashkenazy, Y., Havlin, S., & Schellnhuber, H. J. (2017). Network analysis reveals strongly localized impacts of el nino. *Proc. Natl Acad. Sci. USA., 114*, 7543-7548.
Fan, J., Meng, J., Ashkenazy, Y., Havlin, S., & Schellnhuber, H. J. (2018). Climate network percolation reveals the expansion and weakening of the tropical component under global warming. *Proc. Natl Acad. Sci. USA., 115*(52), E12128-E12134.
Fan, J., Meng, J., Ludescher, J., Chen, X., Ashkenazy, Y., Kurths, J., et al. (2021). Statistical physics approaches to the complex earth system. *Physics Reports, 896*, 1-84.
Fu, Q. (2006). Enhanced mid-latitude tropospheric warming in satellite measurements. *Science, 312*(5777), 1179-1179.
Goe., S. T. (2014). Atmospheric circulation as a source of uncertainty in climate change projections. *Nat. Geosci., 7*(10), 703-708.
Guez, O., Gozolchiani, A., Berezin, Y., Brenner, S., & Havlin, S. (2012). Climate network structure evolves with north atlantic oscillation phases. *EPL, 98*(3), 38006.
Gómez-Gardees, J., D., S.-P., & A., A. (2017). Critical regimes driven by recurrent mobility patterns of reaction–diffusion processes in networks. *Nat. Phys., 14*, 391-395.
Ham, Y. G. (2018). El nino events will intensify under global warming. *Nature, 564*(7735), 192-193.
Helbing, D. (2013). Globally networked risks and how to respond. *Nature, 497*(7447), 51-59.
Helbing, D., Armbruster, D., Mikhaliov, A. S., & Lefeber, E. (2006). Information and material flows in complex networks. *Phys. A., 363*, xi-xvi.
Held, I. M., & Soden, B. J. (2006). Robust responses of the hydrological cycle to global warming. *J. Clim., 19*, 5686-5699.
Hsiang, S. M., C., M. K., & A., C. M. (2011). Civil conflicts are associated with the global climate. *Nature, 476*, 438-441.
Karl, T. R., Knight, R. W., & Plummer, N. (1995). Trends in high-frequency climate variability in the twentieth century. *Nature, 377*(6546), 217-220.
Kjellsson, J. (2014). Weakening of the global atmospheric circulation with global warming. *Clim. Dynam., 45*, 975-988.
Knutson, T. R., Jonghun, K., Fanrong, Z., & Wittenberg, A. T. (2018). Cmip5 model-based assessment of anthropogenic influence on record global warmth during 2016. *B. Am. Meteorol. Soc., 99*(1), S11-S15.
Knutson, T. R., & Manabe, S. (1995). Time-mean response over the tropical pacific to increased co2 in a coupled ocean-atmosphere model. *J. Clim., 8*(9), 2181-2199.
Krause, C. M., Lang, A. H., Laine, M., Kuusisto, M., & Pönn, B. (1996). Event-related eeg desynchronization and synchronization during an auditory memory
task. *Electroen. Clin. Neuro.*, 98(4), 319-326.

Lau, N. C., & Nath, M. J. (1987). Frequency dependence of the structure and temporal development of wintertime tropospheric fluctuations—comparison of a gcm simulation with observations. *Mon. Wea. Rev.*, 115(1), 251-271.

Liang, Z., Ren, Y., Yan, J., Li, D., Voss, L. J., Sleigh, J. W., et al. (2015). A comparison of different synchronization measures in electroencephalogram during propofol anesthesia. *J. Clin. Monitor. Comp.*, 30(4), 451-466.

Lu, J., Vecchi, G. A., & Reichler, T. (2007). Expansion of the hadley cell under global warming. *Geophys. Res. Lett.*, 34(6), L06805.

Ludescher, J., Gozolchiani, A., Bogachev, M. I., Bunde, A., Havlin, S., & Schellnhuber, H. J. (2013). Improved el nino forecasting by cooperativity detection. *Proc. Natl Acad. Sci. USA.*, 110(29), 11742-11745.

Ludescher, J., Gozolchiani, A., Bogachev, M. I., Bunde, A., Havlin, S., & Schellnhuber, H. J. (2014). Very early warning of next el nino. *Proc. Natl Acad. Sci. USA.*, 111(6), 2064-2066.

M., C. E. K. (1999). Characteristics of wave packets in the upper troposphere. part ii: Seasonal and hemispheric variations. *J. Atmos. Sci.*, 56(11), 1729-1747.

M., H. B. (1945). Non-parametric tests against trend. *Econometrica*, 13, 245-259.

M., M. C. (2005). Has the hadley cell been strengthening in recent decades? *Geophys. Res. Lett.*, 32(3), L03809.

Ma, J., Xie, S. P., & Kosaka, Y. (2012). Mechanisms for tropical tropospheric circulation change in response to global warming. *J. Clim.*, 25(8), 2979-2994.

Malik, N., Bookhagen, B., Marwan, N., & Kurths, J. (2012). Analysis of spatial and temporal extreme monsoonal rainfall over south asia using complex networks. *Clim. Dynam.*, 39(3-4), 971-987.

Meel, G. A., Zwiers, F., Evans, J., Knutson, T., & Whetton, P. (2000). Trends in extreme weather and climate events: Issues related to modeling extremes in projections of future climate change *.* *B. Am. Meteorol. Soc.*, 81(3), 427-436.

Meng, J., Fan, J., Ashkenazy, Y., Bunde, A., & Havlin, S. (2018). Forecasting the magnitude and onset of el nino based on climate network. *New. J. Phys.*, 20, 043036.

Min, S. K., Zhang, X., Zwiers, F. W., & Hegerl, G. C. (2011). Human contribution to more-intense precipitation extremes. *Nature*, 470(7334), 378-381.

Mishra, A. K., & Nagaraju, V. (2019). Space-based monitoring of severe flooding of a southern state in india during south-west monsoon season of 2018. *Nat. Haz.*, 97(5804), 949-953.

Morone, F., & Makse, H. A. (2015). Influence maximization in complex networks through optimal percolation. *Nature*, 524(7563), 65-68.

Newman, M. E. J. (2019). *Networks*. Oxford University Press.

O’Connor, J. M., Pretorius, P. H., Johnson, K., & King, M. A. (2013). A method to synchronize signals from multiple patient monitoring devices through a single input channel for inclusion in list-mode acquisitions. *Med. Phys.*, 40(12), 122502.

O’Gorman, P. A. (2014). Contrasting responses of mean and extreme snowfall to climate change. *Nature*, 512(7515), 416-418.

Pachauri, R. K., Allen, M. R., Barros, V. R., Broome, J., Cramer, W., Christ, R., et al. (2017). Climate change 2014: Synthesis report. contribution of working groups i, ii and iii to the fifth assessment report of the intergovernmental panel on climate change. In *Intergovernmental panel on climate change*, *geneva*.

Pastor-Satorras, R., Castellano, C., Van Mieghem, P., & Vespignani, A. (2015). Epidemic processes in complex networks. *Rev. Mod. Phys.*, 87, 925-979.

Pfurtscheller, G., & Da Silva, F. L. (1999). Event-related eeg/meg synchronization and desynchronization: basic principles. *Clin. Neurophysiol.*, 110, 1842-1857.

Phillips, N., & Nogrady, B. (2020). The race to decipher how climate change influenced australia’s record fires. *Nature*, 577(7792), 610-612.
Pierrehumbert R., T. (1986). Spatially amplifying modes of the charney baroclinic-instability problem. *J. Fluid Mech.*, 170, 293-293.

Quan, X. W., Diaz, H. F., & Hoerling, M. P. (2004). Change in the tropical hadley cell since 1950. In (p. 85-120). Springer, Dordrecht.

Quiroga, R. Q., Kreuz, T., & Grassberger, P. (2002). Event synchronization: A simple and fast method to measure synchronicity and time delay patterns. *Phys. Rev. E*, 66(4 Pt 1), 041904.

R., A., & L., B. A. (2002). Statistical mechanics of complex networks. *Rev. Mod. Phys.*, 74, 47-97.

R., C., & S., H. (2010). Complex networks: Structure, robustness and function. In (p. 1-6). Cambridge Univ Press, Cambridge, United Kingdom.

Rheinwalt, A., Boers, N., Marwan, N., K., J., & Werner, P. (2016). Non-linear time series analysis of precipitation events using regional climate networks for germany. *Clim. Dynam.*, 46, 1065-1074.

Schellnhuber, H. J. (n.d.). *The 10 science 'must knows' on climate change*, 23rd conference of the parties (future earth, stockholm). [www.futureearth.org/news/cop23-10-science-must-knows-climate-change](http://www.futureearth.org/news/cop23-10-science-must-knows-climate-change). (Accessed November 13, 2017)

Schleussner, C. F., Donges, J. F., Donner, R. V., & Schellnhuber, H. J. (2016). Armed-conflict risks enhanced by climate-related disasters in ethnically fractionalized countries. *Proc. Natl Acad. Sci. USA.*, 113(33), 9216-9221.

Seo, K. H., Frierson, D. M. W., & Son, J. H. (2014). A mechanism for future changes in hadley circulation strength in cmip5 climate change simulations. *Geophys. Res. Lett.*, 41(14), 5251-5258.

Stolbova, V., Martin, P., Bookhagen, B., Marwan, N., & Kurths, J. (2014). Topology and seasonal evolution of the network of extreme precipitation over the indian subcontinent and sri lanka. *Nonlinear Proc. Geoph.*, 21(4), 901–917.

Tanaka, H. L., Ishizaki, N., & Kitoh, A. (2004). Trend and interannual variability of walker, monsoon and hadley circulations defined by velocity potential in the upper troposphere. *Tel. A. Dyn. Met. Ocea.*, 56(3), 250-269.

Tass, P., Rosenblum, M. G., Weule, J., Kurths, J., Pikovsky, A., Volkmann, J., ... Freund, H. J. (1998). Detection of n:m phase locking from noisy data: Application to magnetoencephalography. *Phys. Rev. Lett.*, 81(15), 3291-3294.

Tebaldi, C., Hayhoe, K., Arblaster, J. M., & Meehl, G. A. (2006). Going to the extremes: An intercomparison of model-simulated historical and future changes in extreme events. *Climatic Change*, 79(3), 185-211.

Tollefson, J. (2015). Severe weather linked more strongly to global warming. *Nature*. (doi: 10.1038/nature.2015.17828)

Tsonis, A. A., & Swanson, K. L. (2008). Topology and predictability of el nino and la nina networks. *Phys. Res. Lett.*, 100(22), 228502.

Vecchi, G. A., & Soden, B. J. (2007). Global warming and the weakening of the tropical circulation. *J. Clim.*, 20, 4316-4340.

Wang, Y., Gozolchiani, A., Ashkenazy, Y., Berezin, Y., Guez, O., & Havlin, S. (2013). Dominant imprint of rossby waves in the climate network. *Phys. Res. Lett.*, 111(13), 138501.

Xie, Z., Black, R., & Deng, Y. (2019). Planetary and synoptic-scale dynamic control of extreme cold wave patterns over the united states. *Clim. Dynam.*, 53(3-4), 1477-1495.

Yamasaki, K., Gozolchiani, A., & Havlin, S. (2008). Climate networks around the globe are significantly affected by el nino. *Phys. Res. Lett.*, 100, 228501.

Yonetani, T., & Gordon, H. B. (2001). Simulated changes in the frequency of extremes and regional features of seasonal/annual temperature and precipitation when atmospheric co2 is doubled. *J. Clim.*, 14(8), 1765-1779.

Yu, B., & Zwiers, F. W. (2010). Changes in equatorial atmospheric zonal circulations in recent decades. *Geophys. Res. Lett.*, 37, L05701.

---

This article is protected by copyright. All rights reserved.
Zhang, Y., Chen, D., Fan, J., Havlin, S., & Chen, X. (2018). Correlation and scaling behaviors of fine particulate matter (PM 2.5) concentration in China. EPL, 122(5), 58003.

Zhang, Y., Fan, J., Chen, X., Ashkenazy, Y., & Havlin, S. (2019). Significant impact of Rossby waves on air pollution detected by network analysis. Geophys. Res. Lett., 46, 12476-12485.

Zhang, Y., Fan, J., Marzocchi, W., Shapira, A., Hofstetter, R., Havlin, S., et al. (2020). Scaling laws in earthquake memory for interevent times and distances. Phys. Rev. Res. (doi: 10.1103/PhysRevResearch.2.013264)
This article is protected by copyright. All rights reserved.
