On the impacts of El Niño events: a new monitoring approach using complex network analysis

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Key Points:

- The El Niño impacts are linked with network phase transition analysis.
- The less-than-expected impacts of the El Niño in 2015/2016 are explained.
- Eastern Pacific and Central Pacific El Niño events are well distinguished.

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Abstract

It is well known that El Niño events can induce worldwide impacts. However, the fact that strong El Niño events do not necessarily induce strong impacts, raises a new research question: how to estimate the impacts of El Niño events in advance? To address this question, we studied the El Niño impacts from the perspective of complex network. By comparing the results from five El Niño events with distinct impacts, we found that the phase transition of the surface air temperature network over tropical Pacific is closely related to the El Niño impacts. This phenomenon was used to explain the less-than-expected impacts of the strong 2015/2016 El Niño, which is suggested more like a Central Pacific-Eastern Pacific mixed El Niño. To monitor the impacts objectively, we further proposed an index, which can be used in real-time operations.

Plain Language Summary

It is well known that El Niño event has substantial impacts on climate, which can induce extreme events or even natural disasters. There are a variety of indices (e.g. Niño3.4 index) to measure the strength of the El Niño, but the fact that strong El Niño does not necessarily mean strong impacts calls for appropriate approaches to quantify the El Niño impacts. Here we proved a close relation between the El Niño impacts and the state of the surface air temperature field over the tropical Pacific. That is, if an El Niño event is not strong enough to significantly alter the state of the upper surface air temperature field, then its influences will not be able to be remarkably transported to remote regions via atmospheric bridges. Using complex network analysis, we quantified the state changes of the surface air temperature field, and proposed a new index to measure the El Niño impacts. The new index well distinguished the Eastern Pacific and the Central Pacific El Niño, and explained the less-than-expected impacts of the 2015/2016 El Niño. Since the calculations are based on past observations, the approach proposed here can be used in operations for objective estimation of the El Niño impacts.

1 Introduction

El Niño has substantial impacts on climate which results in extreme weather phenomena and natural disasters such as floods, droughts and hurricanes (Ward et al., 2014; Siegert et al., 2001; Bove et al., 1998). These impacts are not only limited in local region, but also transported to remote areas worldwide via atmospheric bridges (Horel & Wallace, 1981; Lau & Nath, 1996). Accordingly, it attracts great attention and fruitful findings have been achieved. Although remarkable progresses have been made, there are still issues unsolved. One frequently discussed issue (especially after the 2015/2016 El Niño) is do strong El Niño events always indicate strong climate impacts? By measuring the indices such as Niño3.4 index, the 2015/2016 event is recognized as one of the strongest events that are comparable to other strong events in 1982/1983 and 1997/1998 (Huang et al., 2016; L'Heureux et al., 2017). However, regarding of climate impacts, this strong event was found to have only "moderate to strong" impacts in some aspects (Jacox et al., 2016; Paek et al., 2017; Wu et al., 2018; Zhang et al., 2018). Why the 2015/2016 event did not have comparable climate impacts as the events in 1982/1983 and 1997/1998? Furthermore, previous studies have reported that the Central Pacific (CP) El Niño normally has weaker impacts than those from the Eastern Pacific (EP) El Niño (Banholzer & Donner, 2014; Amaya & Foltz, 2014; Kug et al., 2009; Feng et al., 2011). Can we distinguish the two types of El Niño by investigating their different impacts? Is there a reliable way to quantitatively monitor and warn the potential impacts from El Niño events? All these are still open questions that deserve further investigations.

Recently, complex network has been introduced as a powerful framework for extracting information from large volumes of data, allowing studying the full complexity of the statistical interdependency structure within a multivariate dataset. One can easily construct a climate network using the grid points as nodes and the interactions between the nodes (such as heat, mass, or even information exchanges) as links. Recent works have shown that the climate network method has advantages in revealing the structures of the climate systems (Tsonis et al., 2006; Donges et al., 2009; Radebach et al., 2013), predicting major climate events (Ludescher et al., 2013, 2014; Boers et al., 2014), as well as estimating climate impacts (Yamasaki et al., 2008; Fan et al., 2017). Particularly, a recent work studied the phase transition phenomenon in the surface air temperature (SAT) network over the tropical Pacific and deduced that only when the SAT network collapses under the influences of the underlying sea surface temperature anomalies (SSTA), the impacts of El Niño can be significantly transported to remote regions (Lu et al., 2016; Hua et al., 2017; Lu et al., 2018). This means the phase transition in the SAT network might be related to the remote impacts of El Niño. Is the inference reasonable? From the perspective of phase transition, can we develop an index to monitor the remote impacts of El Niño? These are the questions to be addressed in this work.

Since it is reported that CP events normally have weaker impacts than those from EP events, in this study we first analyzed five El Niño events (two EP and three CP) with distinct impacts. As expected, remarkable phase transitions were found in the SAT network when the EP events (with stronger impacts) occurred. While during the CP events (with weaker impacts), no phase transition was detected. These results confirmed the relations between the phase transition in the SAT network and the El Niño impacts, based on which the less-than-expected impacts from the 2015/2016 event were explained.

The rest of the paper is organized as follows. In section 2, we will briefly introduce the data and the methods used in this paper. In section 3, the phase transition phenomenon in the SAT network over the tropical Pacific will first be shown. After comparing the different phase transition results under different El Niño events, we focus on the 2015/2016 event and try to give an explanation to its less-than-expected impacts. In the end, we propose a new index to monitor the El Niño impacts and conclude this paper in section 4.

2 Data and Methods

2.1 Data

In this study, the daily surface air temperature (SAT) at 2 meters on $2.5^o \times 2.5^o$ grid from 1979 to 2018 was downloaded from European Centre for Medium-Range Weather Forecasts reanalyses (ERA-Interim) (Dee et al., 2011). The SAT network was constructed over the domain 120^oE to 285^oW and 20^oN to 20^oS. In our analysis, every other grid point was selected as a node, and the horizontal resolution of the network is $5^o \times 5^o$ (see red dots in Fig. 1). The monthly precipitation data over land from 1979 to 2016 was downloaded from Global Precipitation Climatology Centre (GPCC) to analyze the El Niño impacts. Besides, the monthly Niño3.4 index and the Southern Oscillation Index (SOI) from Climate Prediction Center (CPC) of National Oceanic and Atmospheric Administration/National Centers for Environmental Prediction (NOAA/NCEP) were also used as indicators of El Niño events.

2.2 Methods

Surface air temperature Network. A SAT network was constructed by calculating the similarity of the SATs at each pair of the nodes. The nodes were marked with numbers from 1 to 306 as node index according to the sequence from west to east and from north to south. Before constructing the network, we first calculated the anomalies by subtracting long-term mean annual cycle $T_k(d)$, where k represents the node index (1-306) and d is the calendar date. For every 30th day t, we then computed the time-delayed cross-correlations for each pair of nodes i and j over 365 days before t, with time lags τ between -200 days and 200 days. The coefficient is denoted as $C^t_{i,j}(\tau)$ and the link strength between nodes i and j is thus defined as (Yamasaki et al., 2008; Gozolchiani et al., 2011)

$$W^t_{i,j} = \frac{max(|C^t_{i,j}(\tau)|) - mean(|C^t_{i,j}(\tau)|)}{std(|C^t_{i,j}(\tau)|)}. \tag{1}$$

According to (Guez et al., 2014), the estimation of the link strength $W_{i,j}^t$ is robust as long as τ_{max} is longer than around 70 days. Therefore, $\tau_{max} = 200$ days was used in our calculations. To check whether a pair of nodes is truly connected, we further determined a threshold Q by shuffling the original time series at each node and repeating the calculations for $1,000$ times. At the significance level of 0.01, the threshold $Q = 5.7$. This means only when the link strength is above the threshold that one can confirm a true connection between the considered two nodes. Using Heaviside function, this definition can be represented as

$$A_{i,j}^t = \theta(W_{i,j}^t - Q) = \begin{cases} 1, & W_{i,j}^t > Q \\ 0, & W_{i,j}^t < Q \end{cases}, \tag{2}$$

Node i is isolated if it has no links with any other nodes. Since the occurrence of El Niño events can break the links in the SAT network and increase the number of isolated nodes (Lu et al., 2016), the percentage of isolated nodes in the total nodes (i.e. 306) at each time point t was calculated as P^t to measure the intensity of the forcings by the underlying SSTA.

Giant component size. To detect the phase transition in the SAT network, an important quantity, giant component size, was studied in this work. This quantity is a measure of the fragmentation and functionality of network (Bashan et al., 2013; Schneider et al., 2011; Albert et al., 2000). To calculate it, one needs to find the largest cluster in the network without isolated nodes, where i) any two nodes can be connected with at least one path, and ii) the number of nodes is the highest. Then the giant component size at each time point t can be defined as (Lu et al., 2016),

$$S^t = \frac{N_{LC}}{306(1 - P^t)}, \tag{3}$$

where N_{LC} is the number of nodes in the largest cluster. The change of S depicts the change of the network state. If S changes suddenly from a high (low) level to a low (high), a phase transition is thus detected.

3 Results

3.1 Phase transition in the SAT network over tropical Pacific

Before going deep into the research of El Niño impacts, we first checked the phase transitions in the SAT network over tropical Pacific under the impacts of El Niño. Figure 1a shows the temporal variation of giant component size S and the percentage of isolated nodes P with Niño3.4 index presented in the bottom. S is significantly and negatively correlated with P. When P increases during an El Niño/La Niña event, S usually decreases significantly, indicating a change of the SAT network. To better illustrate this change, we presented the SAT network at two time points before and during the 1997/1998 event (Fig. 1b and 1c). With the development of the event, the SAT network becomes less connected and broken into several small independent pieces ($S = 0.23$) from a big cluster ($S = 0.96$). This phenomenon indicates the SAT network is converting from a stable to unstable/metastable state due to the effects of this El Niño event.

In order to check whether the changes of S implies a phase transition in the SAT network, we classified all the considered time points (1979-2018) into two groups according to Niño3.4 index. If Niño3.4 index is larger than 0.5, we name them as El Niño cases , otherwise, we name them as normal cases with Niño3.4 index between -0.5 and 0.5. By studying how the S varies with P in the two groups, significant differences were found. In the normal group (Fig. 2b), the S from nearly all the cases are above 0.6. While in the El Niño group (Fig. 2a), the S is divided into two parts that one is above 0.6 and the other one drops abruptly to a lower level (below 0.6) as long as the P is larger than a critical point ($P_c = 0.4$). These results are in line with previous works (Lu et al., 2016; Hua et al., 2017), indicating that phase transitions in the SAT network indeed exist when the impacts from the underlying SSTA are strong enough.

3.2 Phase transition versus El Niño impacts

Although phase transitions are observed in the El Niño group (Fig. 2a), it is found that not all El Niño events correspond to big decreases of S (Fig. 1a), indicating distinct impacts of different events. To test whether the phase transition in the SAT network is related to the El Niño impacts, five El Niño events were analyzed (see the magenta and yellow bars in Fig. 1a). One reason for studying these events is that they are well recognized as two EP and three CP events without disputes (Wiedermann et al., 2016; Yu et al., 2012). As well recognized, the impacts caused by EP events are normally stronger than those by CP events. Besides, their SOI also show great differences (see the green bars in Fig. 1a). The SOI in EP events drop to much lower values than those in CP events, indicating the EP events have stronger impacts. Most importantly, the global impacts of these El Niño events are obviously different. For instance, much more areas are found to suffer from anomalous dry/wet conditions during the two EP events than those during the three CP events (Figs. S1-S3 in the supporting information). Hence, by studying the phase transition in the SAT network under these El Niño events, we obtained some hints about the relation between the phase transition and El Niño impacts. It is worth noting that the state of the SAT network at a give time point t was estimated using data of 365 days before t (see the "Methods" section). It reflects the average responses of the SAT network to the underlying anomalous SSTs, where the information of the potential changes of the SST pattern during the considered period is already included. Similar to Fig. 2a and 2b, we first presented the S and P values during these El Niño events. For the events in 1982/1983 and 1997/1998 (Fig. 2c), the S value first stays at a high level (above 0.6) with $P < 0.4$ at the beginning. With the development of the events, however, S decreases sharply when P approaches 0.4. This is similar to the phase transition in Fig. 2a. For the events in 1994/1995, 2004/2005, and 2009/2010 (Fig. 2d), on the contrary, there is no phase transition observed and all the S values stay at a high level (above 0.6). This result suggests that the CP events cannot induce a substantial state change in the SAT network, which might be also the reason why these events have weaker impacts compared to the EP events. This implication can be understood as follows. The anomalous SST during an El Niño event will first affect the upper SATs at some nodes, and break the links between them and the SATs at other nodes (Fig. 1b, 1c). Once the number of broken links reaches a certain level, the SAT network will experience a phase transition, which may induce a significant change of the atmospheric circulation over the tropical Pacific. In this case, the energy and information of the El Niño event can be more easily transported to remote regions. Accordingly, the phase transition in the SAT network is related to the El Niño impacts.

To better quantify the degree of the phase transition in the SAT network, we further proposed a metric named as the ratio of $S < 0.6$ (RS0.6), which is defined as the ratio of the time points with $S < 0.6$ to all the time points during an El Niño event. By definition, this value is between 0 and 1. If the value is larger than 0, the phase transition is triggered. As shown in Fig. 3, the RS0.6 values for the EP events in 1982/1983 and 1997/1998 are around 0.4 and 0.6 while the RS0.6 values for the CP events in 1994/1995, 2004/2005, 2009/2010 are 0, indicating the phase transitions were only triggered during the EP events. The RS0.6 thus serves as an efficient index to measure the phase transition in the SAT network during an El Niño event. In the following section, we will use this index to study the impacts of the 2015/2016 event.

3.3 Phase transition during the 2015/2016 El Niño event

The 2015/2016 El Niño is considered as one of the strongest events on record. However, the impacts of this event were not as expected. To the end of this section, we will study the impacts of this event using the approaches presented above. Similar to Fig. 2c, the S values in Fig. 2e first stay at a higher level (above 0.6) when P is small. At a certain point, the S values drop suddenly to a low level (below 0.6), indicating a phase transition in the SAT network. However, compared to the phase transitions during the 1982/1983 and 1997/1998 events, there are only three points with S below 0.6. This means the 2015/2016 event took longer time to alter the state of the SAT network, or in other words, the phase transition during this event was weaker. To better support this argument, we further calculated the RS0.6 index (Fig. 3). Different from the results of CP events, the RS0.6 index for the 2015/2016 event is larger than 0. However, compared to the RS0.6 indexes of the EP events, it is much smaller (around 0.2). Accordingly, the 2015/2016 event did not cause a strong phase transition as the two EP events, and its impact may be not fully transported to remote regions via atmospheric bridges. As shown in Figs. S1-S6, we indeed find weaker impacts induced by the 2015/2016 event than those by 1982/1983 and 1997/1998 events, especially in the following summer .

To understand why the phase transition in 2015/2016 is different from those in 1982/1983 and 1997/1998, it is straightforward to look into the SAT network and study the node vulnerability F_i (Lu et al., 2016; Hua et al., 2017; Lu et al., 2018). F_i is a quantity that measures how vulnerable a node i is when the network is influenced. It is defined as the ratio of the times that a given node is isolated to the entire time period. By definition, it ranges from 0 to 1. If the ratio is high, we consider the node is easier to be isolated (high vulnerability). The nodes over the tropical central eastern Pacific have been reported to be more vulnerable as the SSTAs at this region have the strongest influences on the upper SATs (Lu et al., 2016; Hua et al., 2017; Lu et al., 2018). Consequently, node links in this region are easy to break and the nodes are more likely to be isolated. Figure 4 confirms this finding by presenting the spatial distribution of F_i for the six El Niño events. However, compared to the results of EP events (Fig. 4d, 4e), the area with high F_i during the CP events (Fig. 4a-c) is much smaller. The remarkable differences are mainly in two regions. One is in the equatorial center eastern Pacific, and the other is around the western Pacific warming pool. Since the node vulnerability in the SAT network is largely controlled by the underlying SSTA, the different F_i values over these two regions may be related to the different upper ocean heat content distributions during EP and CP events (Timmermann et al., 2018). For EP events, the greater changes of the upper ocean heat content over the tropical western and central-eastern Pacific may result in the high F_i values in these two regions. While for the CP events, the changes of the upper ocean heat content mainly occur over the central Pacific instead of the western and central-eastern Pacific. From Fig. 4, the weaker influences of CP events on these two regions may contribute to the missing of the phase transition in the SAT network, and thus the limited impacts. Regarding the 2015/2016 event, the spatial distribution of F_i is similar to those in EP events but with lower values and smaller areas, especially in the equatorial western Pacific. This El Niño event is more like a CP-EP mixed event, which is consistent with previous studies (Paek et al., 2017; Palmeiro et al., 2017; Chen et al., 2017). This may explain the less-than-expected impacts of the 2015/2016 event. Besides, the western Pacific warming pool is suggested as a key region for further investigation (Jin, 1996; Picaut et al., 1996).

4 Summary and Conclusions

Motivated by the puzzle of why the strong 2015/2016 El Niño did not induce the expected impacts, we studied the El Niño impacts from the perspective of complex network. We found that the impacts of an El Niño event is closely related to the phase transition in the SAT network over the tropical Pacific. Different phase transitions indicate distinct El Niño impacts, and this allows us to distinguish EP and CP El Niño. For the 2015/2016 event, it was found that the phase transition is not as significant as those in 1982/1983 and 1997/1998. By further comparing the results with those obtained during CP events, it was suggested that this event is more like a CP-EP mixed event. More than explaining its less-than-expected impacts, this work further proposed an index, RS0.6, which can be used to objectively monitor the impact of El Niño events.

It is worth noting that the variables such as S^t, P^t at a given time point t, were calculated using data of 365 days before t. In this way, one can monitor the real-time variation of the SAT network state. When an El Niño comes to the end (i.e., in spring of the second year), one can determine whether there is a phase transition and how significant the phase transition is by calculating the RS0.6 index. With these information, the subsequent El Niño impacts on remote regions can be roughly judged.

In the end, we would like to mention that the approach proposed in this work can only judge whether there will be strong impacts in the coming months after an El Niño event. To forecast more precisely which region will suffer the impacts, however, more detailed studies on the teleconnections between the El Niño region and other remote areas are highly required. For this purpose, one potential way is to combine our findings in this work with other analyses, such as the dynamical diagnosis or the study of directed network.

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Data Availability

The authors acknowledge the FAIR data policy. The data used here can be downloaded from these links as follows.

ERA-Interim data provided ECMWF can be accessed at
https://ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era-interim

Monthly precipitation data over land provided by GPCC can be accessed at https://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html

Monthly Niño3.4 index and SOI index provided by CPC NOAA/NCEP can be respectively accessed at https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/detrend.nino34.ascii.txt and http://www.cpc.ncep.noaa.gov/data/indices/soi

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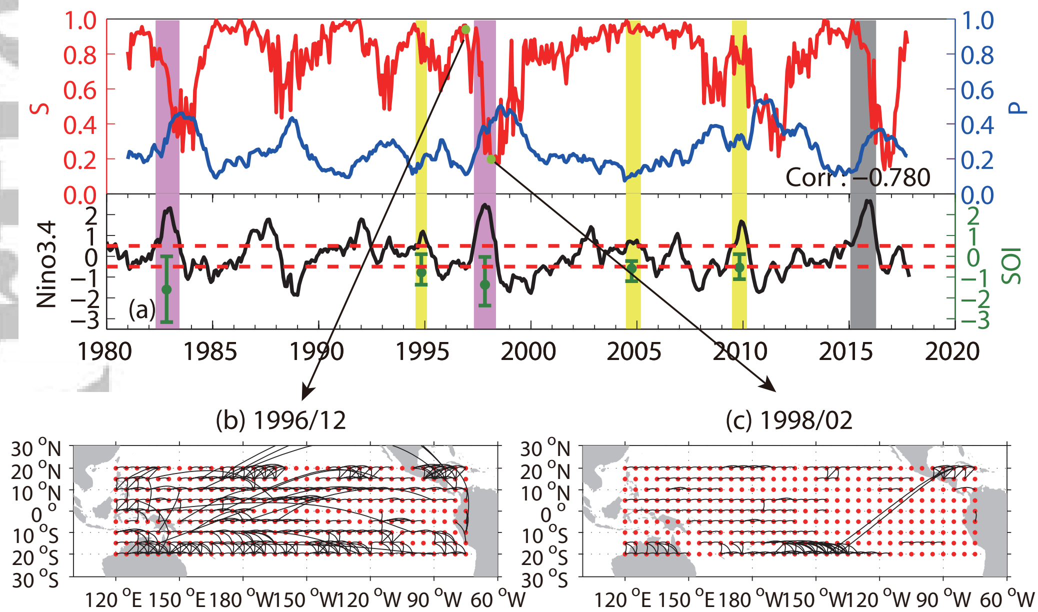

Figure 1. (a) shows the temporal variation of the giant component size S (red), the percentage of isolated nodes P (blue), and the standardized three-month running mean monthly Niño3.4 index (black). The red dashed lines across the Niño3.4 index represent the upper and lower threshold of ±0.5. The magenta, yellow and grey vertical bars represent EP El Niño in 1982/1983 and 1997/1998, CP El Niño in 1994/1995, 2004/2005, 2009/2010, and the El Niño in 2015/2016 respectively. For the two EP and three CP events, the Southern Oscillation Indexes (SOI) are shown as green bars, with the highest, mean, and the lowest SOI values during the event lifetime indicated as the top cap, the middle point, and the bottom cap. P and S are strongly negatively correlated, with the correlation coefficient shown in the figure. (b) and (c) give two examples of the SAT network connection before the El Niño in 1997/1998 at the time point 1996/12, and during the El Niño at time point 1998/02 (see the green points in (a)). The black lines represent the links in the network, and the red dots represent the nodes.

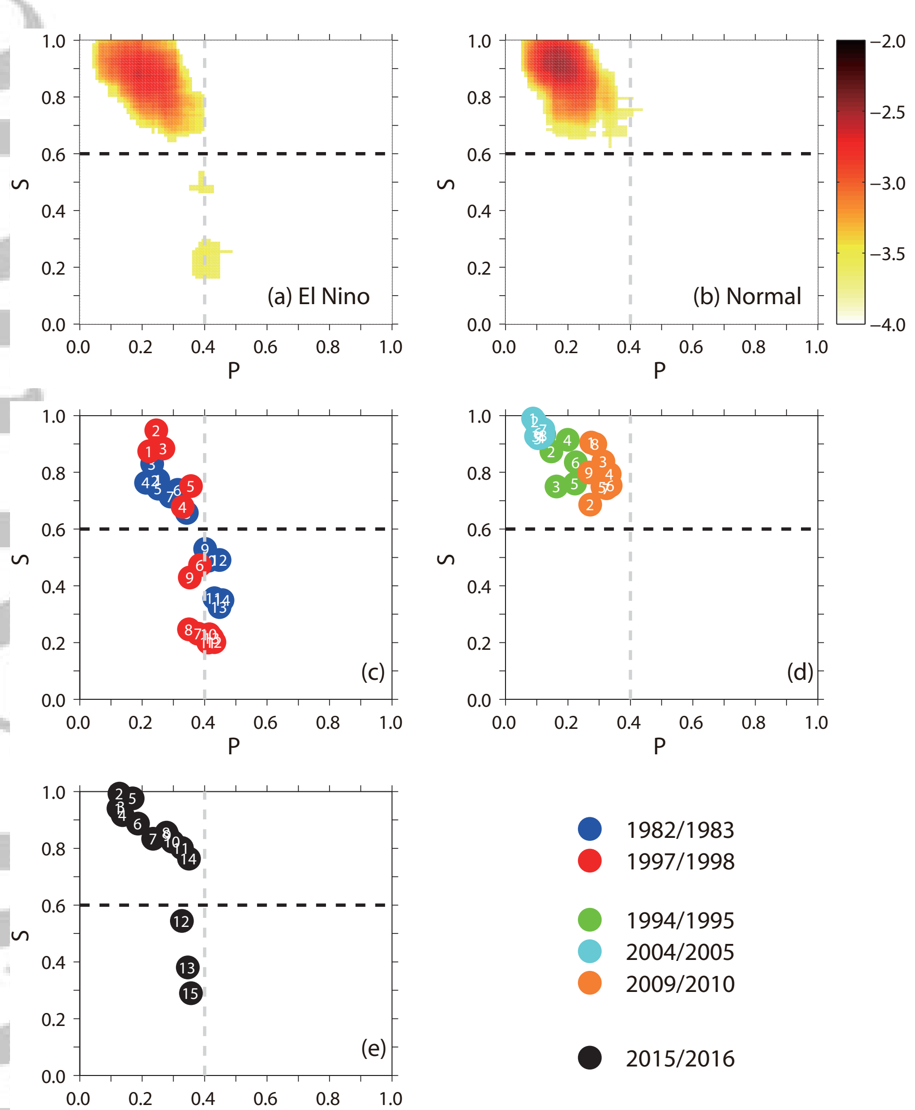

Figure 2. Variation of S with P for (a) El Niño group, (b) normal group and (c)-(e) the selected El Niño events. The two groups are classified according to the Niño3.4 index. The color shown in (a) and (b) represents the probability of having a pair of S and P at a given point of each subfigure. (c)-(e) represent the results for the EP events (blue for 1982/1983, red for 1997/1998), the CP events (green for 1994/1995, cyan for 2004/2005, orange for 2009/2010), and the El Niño in 2015/2016 (black), respectively. The numbers in the dots mark the development sequence of each El Niño event, where "1" shows the first month of the considered event and the biggest number represents the last month. In each subfigure, the black dashed lines represent the boundary of $S = 0.6$, at which the two states of the SAT network are clearly separated (see (a)). The grey dashed lines represent the threshold $P_c = 0.4$, close to which the phase transition may be triggered.

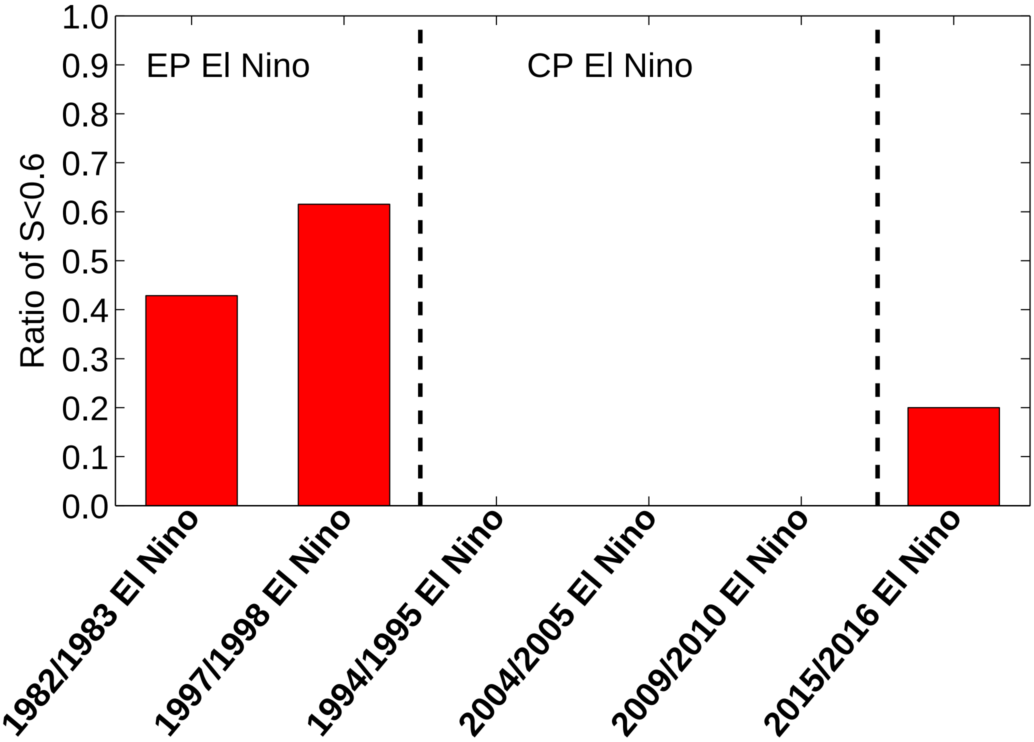

Figure 3. Ratio of $S < 0.6$ (RS0.6 index) for the selected El Niño events. The two blacks dashed lines divide these El Niño events into three groups, the EP events in 1982/1983 and 1997/1998 (left), the CP events in 1994/1995, 2004/2005 and 2009/2010 (middle), and the El Niño in 2015/2016 (right). The higher the RS0.6 index is, the more remarkable the phase transition is.

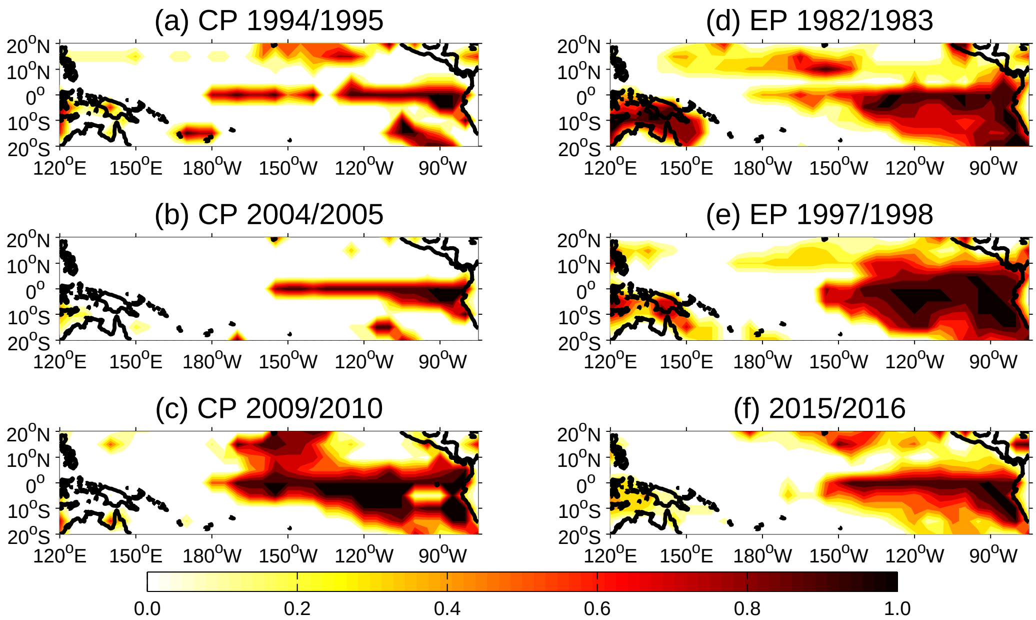

Figure 4. Spatial distributions of the node vulnerabilities F_i in the SAT network for different El Niño events. (a)-(c) show the results of CP El Niño in 1994/1995, 2004/2005 and 2009/2010. (d) and (e) show the results of EP El Niño in 1982/1983 and 1997/1998. (f) shows the results of the El Niño event in 2015/2016. The color shown in each subfigure represents the strength of the node vulnerabilities F_i. For each node, a high F_i means the node is more easily to be isolated during the corresponding El Niño event.