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Complex Network Theoretic Assessment of Precipitation Driven Meteorological Drought in India: Past and Future

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Abstract

Spatio-temporal analysis of droughts is of paramount importance especially for future climate scenarios. We use complex network theoretic measures to understand spatio-temporal properties of precipitation driven meteorological drought across India in past and future climate scenarios. We construct drought networks using Event synchronization (ES) for moderate and extreme drought conditions derived using Standardized Precipitation Index at an aggregated scale of 6 months(SPI-6). Network measures like degree, closeness, betweenness and directionality are used to understand spatio-temporal properties of drought events. ES based networks can capture synchronous events and can help in ascertaining drought propagation through different regions. This study provides insight into the structural properties of drought networks and how they change for projected climate regimes. We find drought hotspots as well as regions which are vulnerable to spatially separated drought events. In the past, regions in western India were vulnerable to extreme droughts, which can propagate from other regions of the country. Use of complex networks also reveal a reversal in drought propagation directions in future climate scenarios. Furthermore, using centrality measures, we also identify regions which aid in drought propagation

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and act as pathways connecting drought hotspots. Thus, changes in structural and topological properties of complex networks can be used to understand the impact of climate change across regions.

Keywords: Drought, Complex networks, Climate Change, Centrality, Drought Propagation

Highlights

1. Introduction

Drought is a natural hazard which occurs primarily due to prolonged deficits in precipitation. They may cover large spatial regions and can exacerbate to prolonged periods which can have disastrous impacts on socio-economic and agricultural sectors. Droughts occur in India with an almost unfailing regularity(Mishra and Singh, 2010*a*; Mallya et al., 2016) and have entailed large economic losses. Prolonged deficits in rainfall can propagate through the hydrological cycle and can lead to droughts in agricultural and hydrological regimes (Van Loon et al., 2014), often with some time lag. Droughts also propagate spatially, and aided by atmospheric processes they can cover large spatial distances(Herrera-Estrada et al., 2017). Thus, droughts become difficult to predict and quantify because of their spatio-temporal evolution and dependence on many climatic and anthropogenic factors(Mishra and Singh, 2010*b*). Knowledge of spatio-temporal patterns of drought is important for mitigation and policy planning, everso more considering projections of increase in extreme events under future climate scenarios(Dai, 2011). It has been predicted that droughts in India will become more widespread and can intensify in many parts of the country(Bisht et al., 2019).

Drought events are generally characterized by their severity, duration and intensity(Yevjevich, 1967; Herrera-Estrada et al., 2017). Several studies have been done to understand drought at regional as well as national scales in terms of their severity and duration. Droughts can be classified into meteorological, hydrological, agricultural, groundwater based on different hydrometeorological variables, for example, precipitation, evapotranspiration, soil moisture, streamflow etc. Based on drought indices derived from these variables, univariate and multivariate frequency analysis has been done in previous studies. The seminal work of Yevjevich (1967) based on run theory paved way for univariate characterization of drought events(Cancelliere and Salas, 2004; Dracup et al., 1980; Tallaksen et al., 2009). Dracup et al. (1980) identified duration and severity as characteristic features of a drought event. As duration and severity have non trivial correlation structure, many multivariate distributions have been used to model severity and duration(Shiau, 2006).These methods construct joint probability distributions based on marginal probabilities of severity and duration.

Droughts generally arise out of interactions between different components of hydrological cycle. Several local and global correlation measures can capture the spatio-temporal connectedness between hydroclimatic processes. These connections also manifest in the temporal evolution or time series of the hydroclimatic variables, like precipitation, streamflow, temperature, evapotranspiration etc. Statistical interdependence between time series of these variables between different spatial locations (nodes) can be ascertained by presence or absence of connections (edges) between them. In the past, linear cross correlation measures were used to quantify statistical interdependence between anomaly time series of different locations(Tsonis and Roebber, 2004; Donges et al., 2009; Gao et al., 2017). However, the non linear nature of climatic processes call for non linear correlation measures. Measures like event synchronization(Quiroga et al., 2002) can capture synchronous occurrences of extreme events. Researchers have used event synchronization based complex networks for understanding teleconnections of extreme rainfall events((Boers et al., 2019)), precipitation events ((Rheinwalt et al., 2016; Malik et al., 2012; Kurths et al., 2019; Boers et al., 2013; Mondal et al., 2020)), rainfall modeling(Jha and Sivakumar, 2017), ocean atmospheric teleconnections(Agarwal et al., 2019),stream flow (Yasmin and Sivakumar, 2018) and drought analysis(Konapala and Mishra, 2017). (Konapala and Mishra, 2017) used complex network to understand drought propagation through network measures like strength, divergence, betweenness centrality and directionality. These measures can help us identify regions which are vulnerable to droughts. Furthermore, these measures can allude to important spatial pathways through which droughts propagate. The topological structure of networks can change in projected climate scenarios. This would manifest in network measures like degree, directionality, betweenness centrality etc. Thus changes in the network structure and properties can help us identify potential hotspots and vulnerable areas.

In this work we study precipitation driven meteorological droughts in India from a complex network perspective. Our aim is to use network theoretic measures to understand spatio-temporal properties of drought in past and future climate scenarios. Historically, droughts in India are more pronounced in Western and Peninsular parts. Mallya et al. (2015) observed an eastward shift even within the historical period. This suggests that the drought events are migrating towards Eastern India and new hotspots are created. Furthermore, agriculturally important regions of Indo-Gangetic plains are becoming prone to droughts(Mallya et al., 2015; Mishra et al., 2016). Using a standardized precipitation index (SPI) at 12 months scale (Jha et al., 2020) performed copula based frequency analysis of droughts in India. It was reported that western and central India have a higher return period and it was found that different areas have different resilience to exacerbating drought conditions. This suggests that some regions are more vulnerable to droughts and can aid in either mitigation or propagation of drought to other regions. Under changing climate, droughts are believed to intensify in many parts of the world. Spinoni et al. (2020) used various drought indices to show an intensification of drought over various parts of the world. However, they also showed that use of only precipitation data may not provide a complete picture. Using NASA-NEX downscaled climate ensemble data (Ahmadalipour et al., 2017) showed that under RCP4.5 and RCP8.5 there may be aggravation in severe and extreme drought events over United States. In the context of Indian region, several studies have shown that the spatial hotspots of drought may change from western to eastern parts of the country. Using a non stationary SPI (Salvi and Ghosh, 2016) showed that central, eastern and southeast coastal regions of India are likely to show an increase in extreme dry spells under different RCP2.6, RCP4.5 and RCP8.5. Gupta and Jain (2018) showed that a shift of drought hazard is likely to occur in projected climate scenarios from central India towards southeast-central India. These observations of shift in the hotspots is also observed in study using bias correction approach in which it is shown that drought events are expected to increase in west central, peninsular and central northeast regions of India(Ojha et al., 2013*a*). Motivated by these studies, we ask if complex networks can reveal the shifting of drought hotspots in future climate scenarios. Since, complex networks can provide directionality measures based on synchronous events, we can understand "sources" and "sinks" of drought events. In the context of these studies, it also becomes imperative to understand droughts as complex systems, arising out of spatio-temporal interactions of atmospheric, hydrological and anthropogenic processes.

We present one of the first studies on application of complex networks to understand droughts in India and try to explain recent observations of shift in drought hotspots. We use past and future rainfall data to construct event synchronization based drought networks. Then we use drought networks to derive network properties like indegree, outdegree, closeness and betweenness centrality and directionality. These measures are then used to understand vulnerability of moderate and extreme droughts over India and potential hotspots in future climate scenarios. We use directionality to find dominant propagation directions and use these to ascertain shift in drought hotspots. The article is organized as follows: In section 2 we present the datasets used and the study area. In the next section 3 we present a brief overview of construction of complex networks for climatic and drought data using precipitation and different network measures that we use. We present our results in section 4 in which we use network measures to compare and contrast structural properties of drought networks in past and future climate scenarios. This is finally followed by section 5 in which we discuss our results, limitations and future directions.

2. Study Area and Datasets

2.1. Study Area

The study area is comprised of different river sub-basins of India which include those in Himalayan, Deccan, Coastal, Central, North-Western and Eastern regions. A total of 97 sub basins are defined as per the report of India WRIS (Bhawan and Puram, 2014) obtained from National Remote Sensing Centre, India. The study area shown in Figure 1 encompasses varying agro-climatic zones.

2.2. Datasets

In this study, monthly rainfall data for the historical period (1901-2013) and for the future climate projections (2006-2099) has been used. The historical monthly gridded ($0.25^o \times 0.25^o$) was obtained from Indian Meteorological Department. For the future climate scenarios, we have used the subset of bias corrected, statistically downscaled, gridded ($0.25^o \times 0.25^o$) long term projections released by NASA, called the "NASA-Earth Exchange Global Daily Downscaled Projections" (NEX-GDDP) (Thrasher and Nemani, 2015) over Indian region. These datasets contain downscaled climate projections derived from GCM simulations of CMIP5 under RCP(Representative Concentration Pathway). It has been suggested that NEX-GDDP performs better on monthly scales than daily scales (Raghavan et al., 2018). At local to regional scales, NEX-GDDP serves the purpose for climate change studies and improves upon many of the biases in CMIP5(Sahany et al., 2019). To study precipitation driven meteorological drought, we convert the monthly rainfall time series to Standardized Precipitation Index (SPI) at a 6 month aggregated scale. SPI has been widely used to quantify drought and is calculated based on a long time series rainfall data. Firstly, a probability distribution is fitted to the cumulative rainfall followed by an equiprobability transformation(McKee et al., n.d.). SPI is computationally easy to calculate and different aggregated scales at 3, 6, 9 and 12 months can act for proxy for different hydro-meteorological processes. SPI-6 is effective for capturing. SPI-6 has earlier been used for multivariate drought analysis over India(Ganguli and Reddy, 2014). While SPI is effective for capturing drought in historical periods, it is not effective for capturing droughts in future climate scenarios as it does not take into consideration prospective changes due to temperature variations. However, since we are interested in precipitation based drought, the use of SPI-6 can help in understanding medium term trends in dry spells and precipitation anomalies which may manifest as meteorological drought. In an earlier study, a non stationary SPI (Salvi and Ghosh, 2016) was used to access extreme dry and wet spells in the 21st century. Recently, (Tan et al., 2020) used SPI over Kenya to assess meteorological drought in near, mid and far future. Zhao et al. (2020) used SPI at one month scale to study meteorological drought in North America under projected climate scenarios. SPI at different time scales has been used to study drought characteristics over South Korea under RCP 4.5 and RCP 8.5 scenarios(Choi et al., 2016). In this study, a moderate drought is defined when $SPI_6 \in (-1, -2)$ and an extreme drought is defined for $SPI_6 < -2$.

3. Complex Networks in Climate

Spatio-temporal propagation of droughts(Van Lanen et al., 2013; Van Loon et al., 2014) imply a sense of causality or causal connectivity (Wright, 1921) which can be captured through some linkage between the two spatio-temporally separated processes. Since the linkage implies some correlation between the events at different spatial locations, there have been many statistical and information theoretic measures to quantify the correlation and interdependence of events. Hydrometeorological phenomenon can be understood as manifestation of the underlying dynamics in form of time series of the variable(Tsonis and Roebber, 2004). The correlation between two time series can be used to construct the complex network. However, Pearson correlation is not suitable for plethora of climatological data, owing to it's assumption of the underlying probability distribution of the data.

3.1. Event Synchronization based Complex Network

Generally, extreme events can be synchronized across spatial scales and Event Synchronization (ES) has been used to construct complex networks of streamflow(Yasmin and Sivakumar, 2018), droughts(Konapala and Mishra, 2017), extreme rainfall events(Boers et al., 2013). ES allows for a dynamic delay between events, with an upper bound of allowed delay (τ_{max}) and does away with the inherent assumption of probability distribution of the data. In this study we construct a ES based complex network of precipitation driven meteorological drought in past as well as under projected climate scenarios across 97 basins of India. The first step is the extraction of event time series at each spatial location and then calculating the pair wise dynamic delay. The event time index at location(s) $i(j)$ is given by $t_{i(j)}^{\mu(\nu)}$, where $\mu(\nu) = 1, 2, ...n_i(n_j)$. n_i and n_j are the number of events that occur at locations i and j. Thus the dynamic delay between these spatial locations is given by:

$$\tau_{ij}^{\mu\nu} = min \left\{ \frac{t_i^{\mu+1} - t_i^{\mu}, t_i^{\mu} - t_i^{\mu-1}, t_j^{\nu+1} - t_j^{\nu}, t_j^{\nu} - t_j^{\nu-1}}{2} \right\} \tag{1}$$

The events at i and j are said to be synchronous if $t_i^{\mu} - t_j^{\nu} \in (0, \tau_{ij}^{\mu\nu}) \wedge (0, \tau_{max})$ and under this condition, $S_{ij}^{\mu\nu} = 1$, otherwise $S_{ij}^{\mu\nu} = 0$. A measure of number of synchronous events occurring at i before m is given by:

$$ES_{ij} = \frac{1}{n_i} \sum_{\mu\nu} S_{ij}^{\mu\nu} \tag{2}$$

and, similarly for ES_{ji}. It is a measure of the likelihood of an event propagation from one location to another. Concomitantly, top five percent values of the ES scores are selected (Malik et al., 2012). Once the threshold value of ES is decided, values above the threshold are retained whilst the rest are removed to construct a weighted adjacency matrix (A_{ij}), preserving the directionality(Rheinwalt et al., 2016; Konapala and Mishra, 2017). This adjacency matrix is a binary matrix with the non zero values signifying existence of a link and hence significant synchronization of events at the two spatial locations.

3.2. Network Measures

We use different measures derived from the theory of complex networks to ascertain the structural properties of drought networks constructed from the ES matrix. In this study we primarily use centrality measures like degree, closeness, betweenness alongwith directionality and distance. The degree centrality can be further classified as indegree (D^-) and outdegree (D^+) for directed networks. D^- is the number of the edges that are inward to the node and D^+ is the number of outward edges from the node. More the number of outward edges (greater D^+), more is the ability of that node to propagate an event to other locations. Similarly, D^- can be thought of as a measure of a location to be vulnerable to incoming synchronous events from other regions. Such regions, thus act as "sinks" ($D^- - D^+ > 0$) and "sources" ($D^- - D^+ < 0$), characterized by their differences in degree centrality. For weighted networks, the strength divergence has been used to ascertain the vulnerability of a region to incoming or outgoing events (Konapala and Mishra, 2017; Kurths et al., 2019; Boers et al., 2013). It has also been suggested (Ozturk et al., 2019) that degree can also be used to understand the extent of localization of atmospheric processes over certain regions, which again depends on the topographic structures across the region(Malik et al., 2012). While degree and strength can allude to sources and sinks in the network, betweenness centrality (BC) can help in understanding information transfer pathways of the network and it is assumed that the information propagates along the shortest paths. Mathematically, it is defined as:

$$BC_v = \sum_{i,j \neq v}^{N} \frac{\sigma_{ij}(v)}{\sigma_{ij}} \tag{3}$$

where, σ_{ij} is the number of shortest paths from i to j, that include the vertex v. Another important measure is closeness (C_i), which is the inverse of the average distance between node and it's neighbours.

$$C_i = \frac{1}{\sum_{j=1}^{N} d_{ij}} \tag{4}$$

where d_{ij} is the distance between two nodes, i and j. For a directed graph, we can similarly define incloseness (C^{in}) and outcloseness (C^{out}). A node with higher C^{in} can be easily reached from other nodes and those with a higher C^{out} can easily reach other nodes. Thus, a difference, $C^{in} - C^{out}$ can measure the "reachability" of a node. Nodes with a higher positive(negative) closeness difference would be more likely to allow information transfer, in our case, drought event, to(from) that node. Thus, this can provide information about drought propagation pathways across the regions. Previously, it has been shown that closeness centrality can be used to find pathways of development of extreme rainfall events and it's spatial relation with other systems(Ozturk et al., 2019). Some nodes can spread or aid in propagation of drought events more efficiently than others, as closeness centrality measures the efficiency of a node in spreading the information. Another measure of importance is the link distance $d(i, j)$ which is a great circle distance between the geographical locations. Directionality ($\theta(i, j)$) and distance which have been defined along the dominant links are used to identify out-propagation directions of the event. For this, the dominant direction is identified along the link which has the maximum strength (derived from weighted adjacency matrix)

3.3. Constructing Drought Networks

In this study, we derive the events based on SPI at an aggregated scale of 6 months (SPI_6). The SPI-6 time series represents the precipitation anomaly over the region. We are mainly interested in understanding dry spells of precipitation which can manifest as meteorological drought. The SPI_6 time series is used to study two kinds of events, moderate droughts ($-1 < SPI_6 < -2$) and extreme droughts ($SPI_6 < -2$). These events are extracted from the SPI time series and the event synchronization matrix is constructed for moderate as well as extreme drought events for past (1901-2013) and projected climate scenarios (RCP4.5, RCP8.5). The time series of the sub-basins are assigned at their respective centroids, which act as node of the drought networks. Event synchronization scores for all the pairs are evaluated based on the formalism discussed in the previous sections (section 3.1) and only the top five percent scores are selected. This choice also manifests from the not so large number of nodes (97×97) that are present in our analysis. We impose a τ_{max} of 3 months which is reasonable and has previously been used for the drought networks in US (Konapala and Mishra, 2017). Thus all the values below the threshold are made 0 and only the strongest ES values are kept. Then the adjacency matrix was constructed and the other network measures derived for past and future drought networks in moderate and extreme classes.

4. Results

Historically, drought prone regions in India are in the western, north-western, central India. It was found that while all regions are at risk of exacerbated drought conditions in future, some regions in central northeast, west central and peninsular India may be especially prone to severe drought events in future(Ojha et al., 2013*b*). It is also evident from Figure2a, 2b and 2c, where in the past extreme drought events were found to occur more in the western, central and south peninsular India. Agriculturally important regions of the Indo-Gangetic plains are also prone to extreme meteorological droughts. In the RCP 4.5 scenario (Figure 2b), eastern regions are found to be have more extreme droughts as compared to the western regions. This signifies a spatial shift in the drought occurrences in future climate scenarios. It has been reported earlier that (Salvi and Ghosh, 2016) extreme dry spells (calculated using both SPI and a non stationary version of SPI) are likely to increase over central, eastern, southeast coastal regions under projected climate regimes. These regions are also more likely to witness increased drought occurrences under RCP 8.5 scenarios.

4.1. Centrality Measures of Droughts in Past

Western regions have a higher indegree(Figure4a) as compared to other regions, suggesting that the region is prone to have extreme drought events preceded by extreme droughts in other regions. However, the outdegree of these regions (Figure4b) is also higher than other regions. This suggests that the drought events in western part of the country are localized and not so likely to propagate to farther regions in the South and East. Extreme drought events in western parts may be a result of preceding extreme droughts in other regions as can be seen from the dominant direction of propagation (Figure 3f). Majority of the sub basins have their outward propagation directed towards the western parts of the country. These directions were arrived at using the most dominant event synchronization scores for the respective links. This shows that in past, drought events in Eastern regions propagated through the sub basins with high betweenness centrality (Figure 3e) towards the western regions. Eastern regions comprise of basins like Damodar, Brahmani, Mahanadi, Subarnrekha etc (Bhawan and Puram, 2014) and they have a higher number of outgoing links than incoming links for extreme droughts (Figure 3c). Thus, they have a negative degree difference and act as sources of extreme drought events. Some basins along the western coast also show a negative degree difference and can aid in propagating drought events to Rajasthan and Gujarat states of India, which is also shown in dominant outdirections. In the context of extreme rainfall events in India, previously closeness centrality was used to identify regions which aid in information transfer and potential hotspots which aid in propagating events through the network(Malik et al., 2012). Information flow in the case of climate networks is in the form of energy and matter transport. Similarly, in Figure 3d we show the difference between incloseness and outcloseness centrality($C^{in} - C^{out}$). Regions with positive difference are those which have a higher incloseness centrality. Evidently, regions in the Western part, central India, Indo-gangetic plains have a positive closeness difference. Whereas, eastern regions have a higher outcloseness centrality than incloseness. This suggests that, it is thus easier for eastern regions to propagate extreme drought to the western regions. Peninsular regions are more prone to moderate drought events which is also shown in the closeness maps. A moderate drought event initiated elsewhere is more likely to propagate to the peninsular parts. An extreme drought event initiated in the eastern, southern regions can quickly lead to an initiation of extreme droughts in the western parts of the country. Even in the past, there has been a significant shift of the drought hotspots to the coastal regions of South India, central India and agriculturally important regions of Indo-Gangetic plains (Mallya et al., 2016). These regions also show a higher betweenness centrality, thus acting as important pathways for the propagation of droughts.It is found that sub-basins in central India (Narmada), south east coastal regions are more affected by moderate drought events and have a positive degree difference (Figure 6a).

4.2. Centrality Measures of Droughts in Future Climate Scenarios

Earlier studies have reported that on a long term basis, Indo-Gangetic plains, central India, upper peninsular India would be more severely affected with drought under projected regimes (Bisht et al., 2019). The changes in topological structure and network properties can help in ascertaining future hotspots and changes in propagation patterns if any. While the higher degree regions were mostly localized in the western parts of the country in past, under both RCP 4.5 and 8.5, there is a localization in the eastern and central parts of the country in the degree field(4a, 5a). Regions in the Eastern India (states of Eastern Uttar Pradesh, Bihar, Jharkhand, West Bengal, Odisha) have higher indegree than other regions, while those in central-east area (upper Narmada region, Mahanadi basin) have a higher outdegree. Thus, the eastern regions are more likely to exhibit extreme droughts when an extreme drought is initiated in regions with higher out degree, like the central east and western region. Under RCP 8.5 scenario, this localization becomes ever so evident as the regions with a higher indegree are concentrated in the eastern region and throughout the central India, whereas those with higher outdegree are in the western part of the country. A closer look at the degree difference (Figure 4c) suggests that the sub basins in central east India (Narmada, Tapi) and Southern Indo-Gangetic plains have a higher degree difference and thus are likely to be affected by extreme droughts occurring elsewhere in the western regions and peninsular parts of India under RCP 4.5 scenario. The degree difference is starker under RCP 8.5 scenario (Figure 5c) suggesting that much of central, eastern and peninsular India have higher likelihood of extreme droughts if an initiation of extreme drought occurs elsewhere. Different regions can aid in the propagation of extreme and moderate drought events differently, for example some regions which have a positive degree difference in extreme droughts, show a negative difference in moderate category. This adds to the complexity of spatial propagation of drought and one of the reasons as to why it is difficult to predict the onset of drought and subsequent propagation(Konapala and Mishra, 2017). Furthermore, we find that there is change in the closeness difference of the regions in projected scenarios. Under extreme drought, Eastern regions have a positive C_i difference as compared to past (Figure 4d,3d,5d). This also strengthens the argument that these regions would be more likely to act as extreme drought sinks in future. However, they are more likely to act as drought sources and initiators of moderate drought, propagating the events towards south (Figure 6d,6f,6b). Compared to past, much of the regions in South India show increased vulnerability to moderate drought events and can exhibit moderate droughts if a moderate event occurs synchronously elsewhere. Regions in Northwest India and western India may also be vulnerable to moderate droughts under both the projections. It is also interesting to note that (Preethi et al., 2019) found that under projected scenarios, reduction in rainfall over central and north central India can lead to intensification of droughts in these regions. This may be attributed to the westward shift of the monsoon trough in the drought years, thus leading to an intensification of drought events over central India. As is also evident from our results using complex network theoretic measures, much of central and east India has higher vulnerability to drought events and are an important pathways for spatial drought propagation. North central India has a high betweenness centrality under RCP 4.5 scenario for both extreme and moderate droughts. This may allude to the importance of this region in aiding drought propagation and thus acting as an important pathway. An important study linking these measures to the physical processes was done by (Mondal et al., 2020) in the context of extreme rainfall events in US. It is important to identify moisture transport pathways and their significance in the terms of network measures. Directionality derived using dominant direction for future extreme droughts (Figure 4f, 5f) shows that there is a marked changed in out propagation direction compared to past. While in the past there was an overall western trend of out propagation, most of the out directions point towards central, eastern India and Indo-Gangetic plains under both future projections. Central India under both RCP scenarios are likely to be affected by spatially separated moderate drought events (Figure 6c,6e). Compared to the past, southeast coastal regions may become more vulnerable to incoming moderate drought events. This also signifies that in future, moderate drought events may become more widespread. Another difference between the past and future climate scenarios is in the out propagation distance ($d(i, j)$) distribution shown in Figure 7a-7f.

5. Discussion and Conclusions

In this work we used complex networks based analysis to assess spatial-temporal patterns of precipitation driven meteorological droughts in past and future climate scenarios across India. Motivated by previous works which point to changes in drought hotspots in future climate scenarios across India, we analyzed network theoretic measures to show that complex networks can be used to identify prospective hotspots.

Consistent with previous works on historical drought (Mallya et al., 2016), we find that extreme droughts were more pronounced in western and north-western India. We found that in the past, dominant directions of propagation pointed towards the western parts of the country. Using differences in indegree and outdegree, incloseness and outcloseness we showed that the western regions acted as "sinks" of drought events originating elsewhere, primarily from the eastern and central regions. An interesting finding was the general reversal of this trend in future climate projections under RCP 4.5 and RCP 8.5, wherein we found that most of the eastern and central regions were vulnerable to droughts occurring elsewhere. This can be attributed to increased vulnerability of these regions to initiation of droughts elsewhere. We also identified some sub basins of Indo-Gangetic plains and central India as regions with high betweenness centrality, thus they can be identified as mediators or important pathways through which droughts propagate from one region to another. (Salvi and Ghosh, 2016) identified that under future climate scenarios, central, eastern and southeast coastal regions may experience increased extreme dry spells. This is also corroborated with our study using complex networks that these regions may act as drought sinks in future and thus are vulnerable. We also found that most of the regions may be prone to moderate drought and were likely to exhibit moderate drought following synchronous events elsewhere. In general we found that regions in peninsular India acted as sinks for moderate drought events and were likely to act as sinks in future.

While we showed that some regions are more likely to aid in propagation of droughts than others, the study has it's limitations. First and foremost, we do not consider drought indices which take into consideration the effect of temperature changes in future climate scenarios. While SPI can be used to monitor historical droughts, it has it's limitations in future regimes when temperature changes also come into play(Spinoni et al., 2020, 2018). For this, it is advised to use indices like SPEI which also take into consideration potential evapotranspiration. Taking a SPEI-12 indicator, (Gupta and Jain, 2018) used copulas to model Severity-Duration and Frequency curves over entire India under projected climate scenarios. They found that eastern India, some regions in Gangetic plains and region comprising central, peninsular and southern India may face increased drought severity. This is also corroborated by our study albeit with

SPI-6.Furthermore, we used NEX GDDP projections and it would be interesting to use other model outputs and an perform an intercomparison between the same. Some notable studies have tried to link geo-physical processes with the network measures (Mondal et al., 2020) and it would be interesting to identify such processes and whether drought measures can help in understanding these processes like moisture transport, catchment characteristics which can make some regions more vulnerable to droughts. Some differences in dry spell lengths have been predicted in projections from NEX GDDP and CMIP5 over central India (Jain et al., 2019). Thus, analysis of different models can be done to ascertain any possible biases arising out of model uncertainties. Overall, our study aims to understand the spatial patterns of moderate and extreme drought events driven by precipitation deficits over Indian region in past and future. This is used to identify potential hotspots and important regional pathways which aid in drought propagation which can prove useful for drought mitigation strategies.

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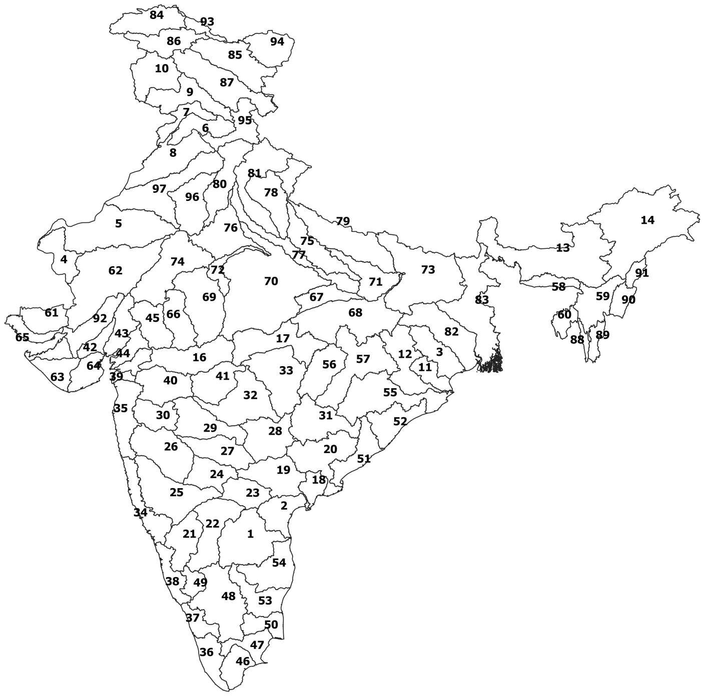

Figure 1: Study area with respective sub basin id represented by node number. The centroid of the sub basin is chosen as the representative node of the entire sub basin.

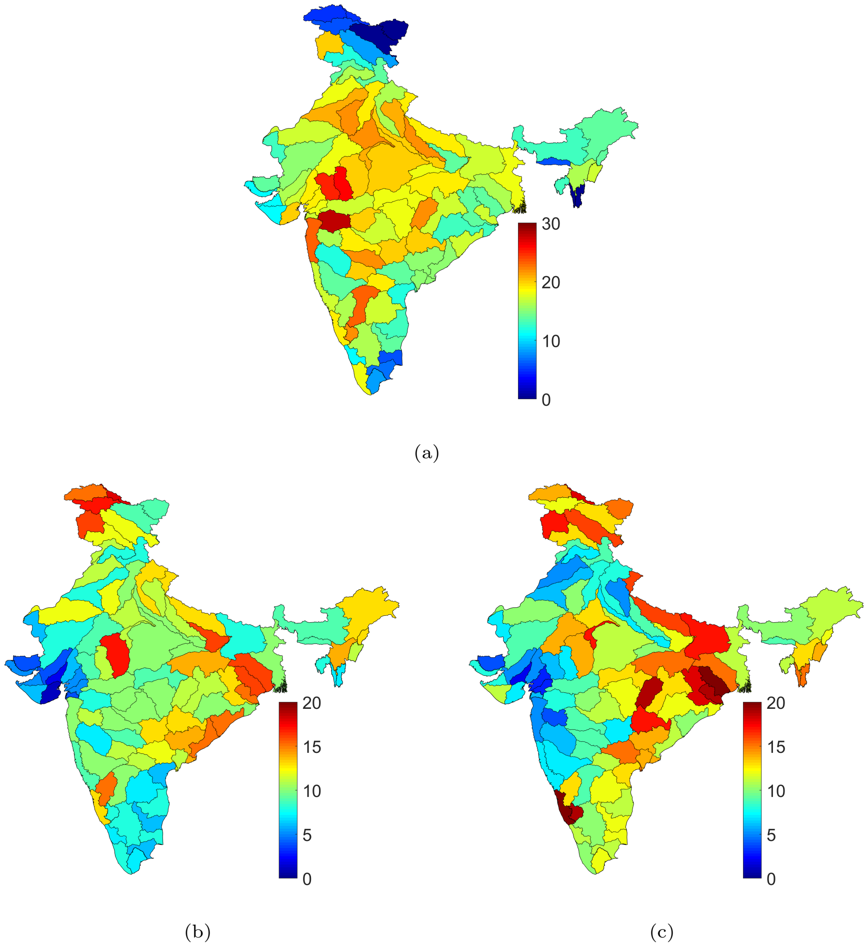

Figure 2: Number of extreme drought occurrences in a) Past b) RCP 4.5 and c) RCP 8.5 scenario.

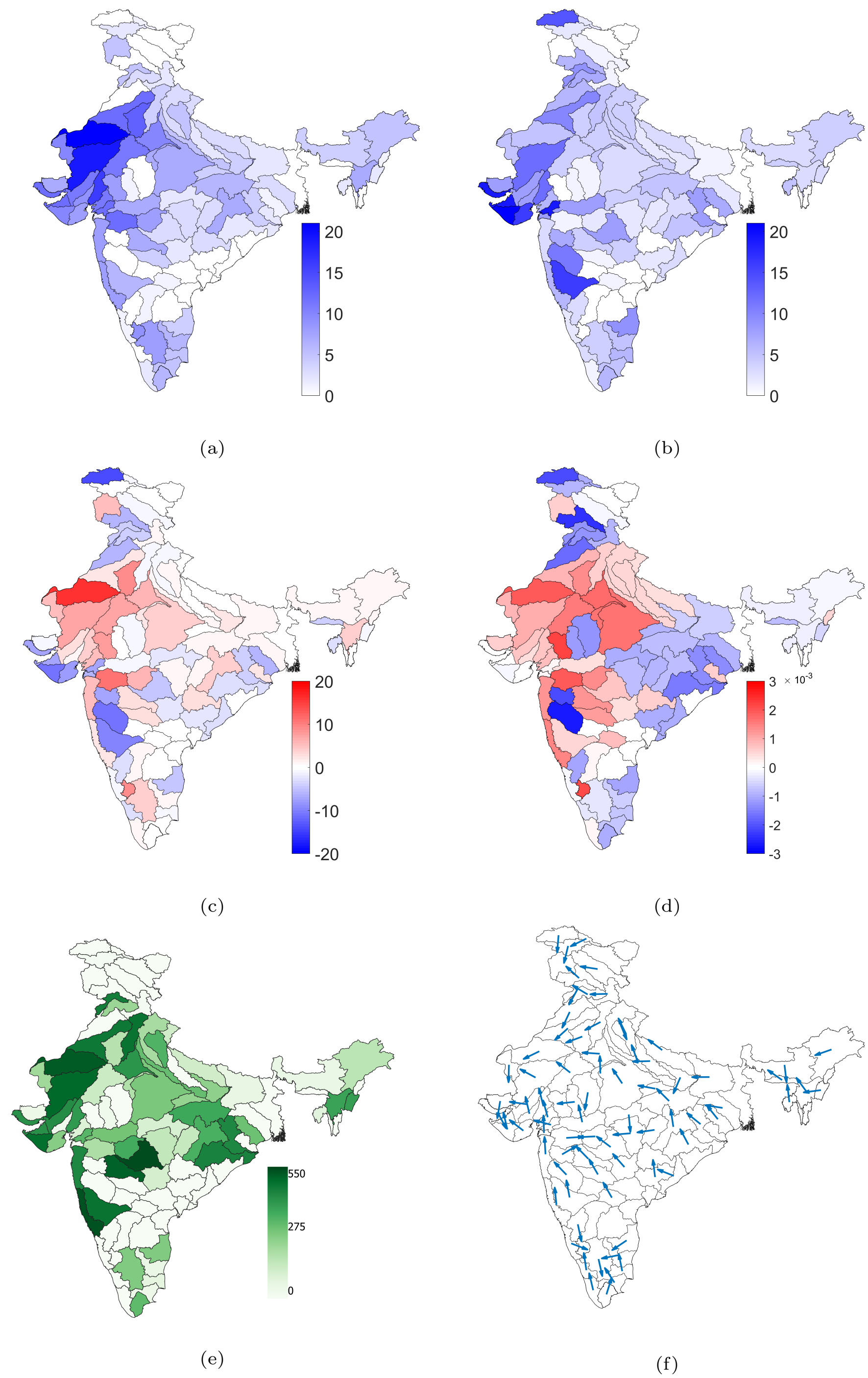

Figure 3: This figure shows different complex network measures of extreme droughts($SPI_6 < -2$) in the past. a) Indegree b) Outdegree c) Degree difference d) Closeness difference e) Betweeenness centrality and f) Dominant out direction

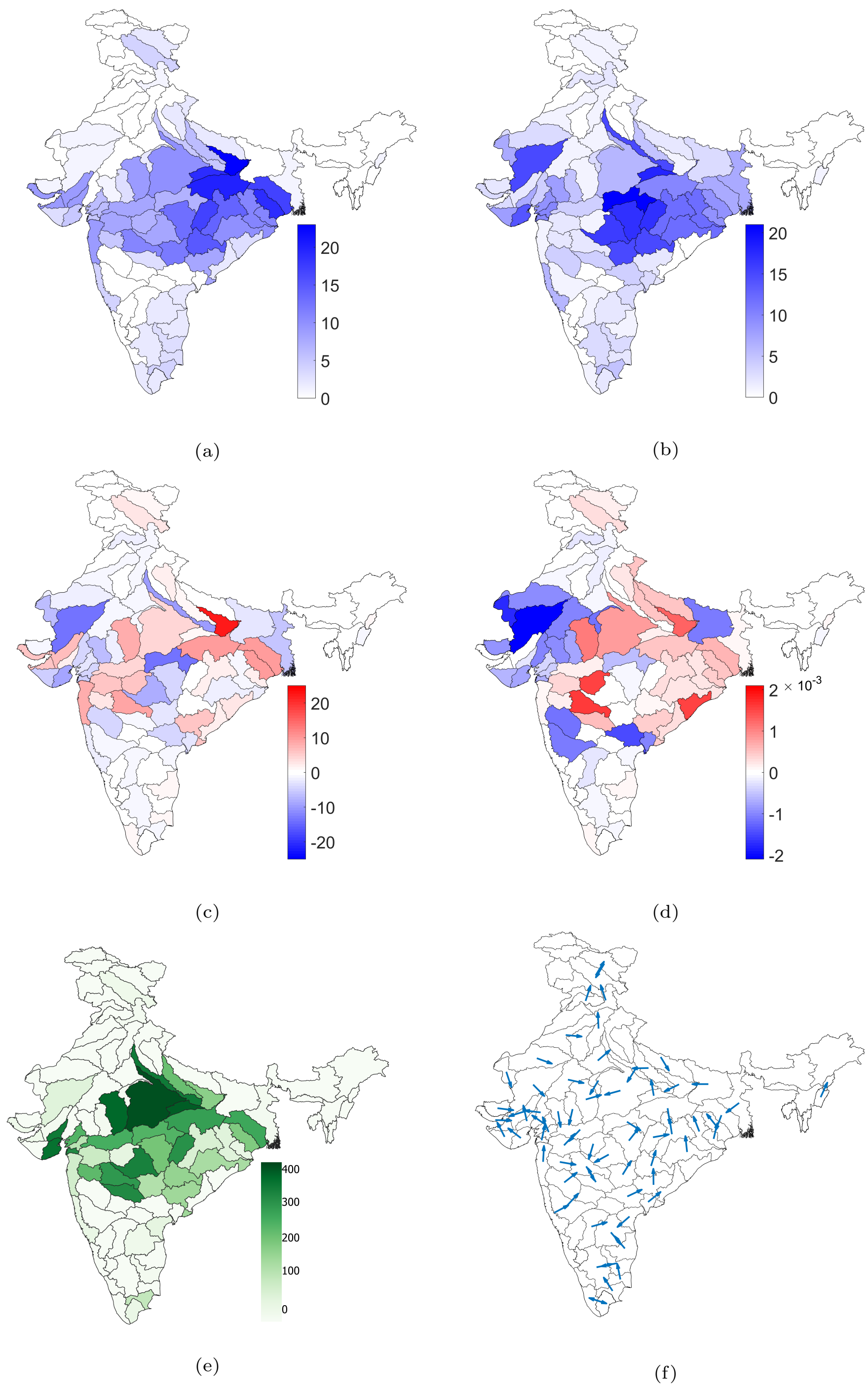

Figure 4: This figure shows different complex network measures of extreme droughts ($SPI_6 < -2$) under RCP 4.5 scenario. a) Indegree b) Outdegree c) Degree difference d) Closeness difference e) Betweeenness centrality and f) Dominant out direction

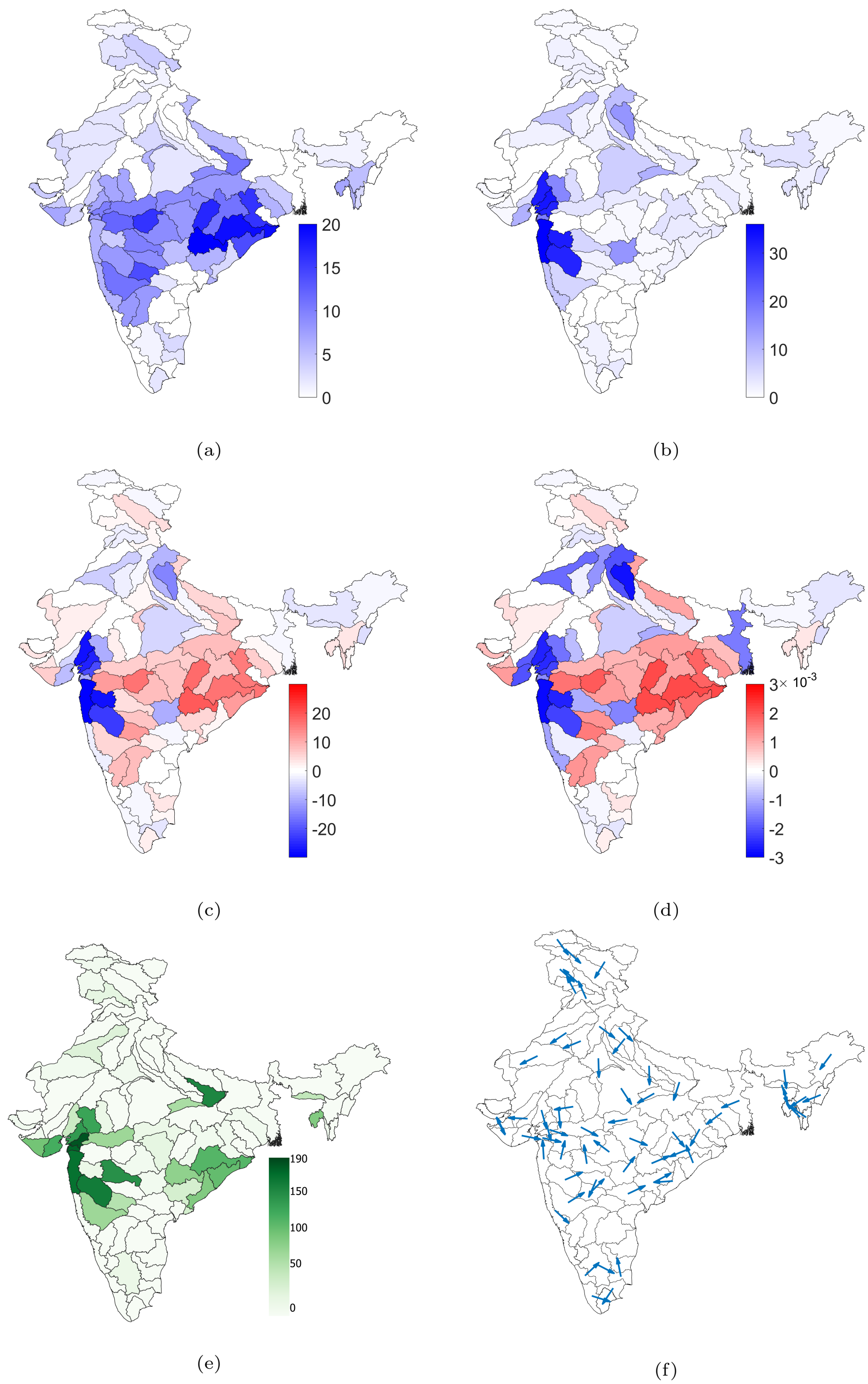

Figure 5: This figure shows different complex network measures of extreme droughts($SPI_6 < -2$) under RCP 8.5 scenario. a) Indegree b) Outdegree c) Degree difference d) Closeness difference e) Betweeenness centrality and f) Dominant out direction

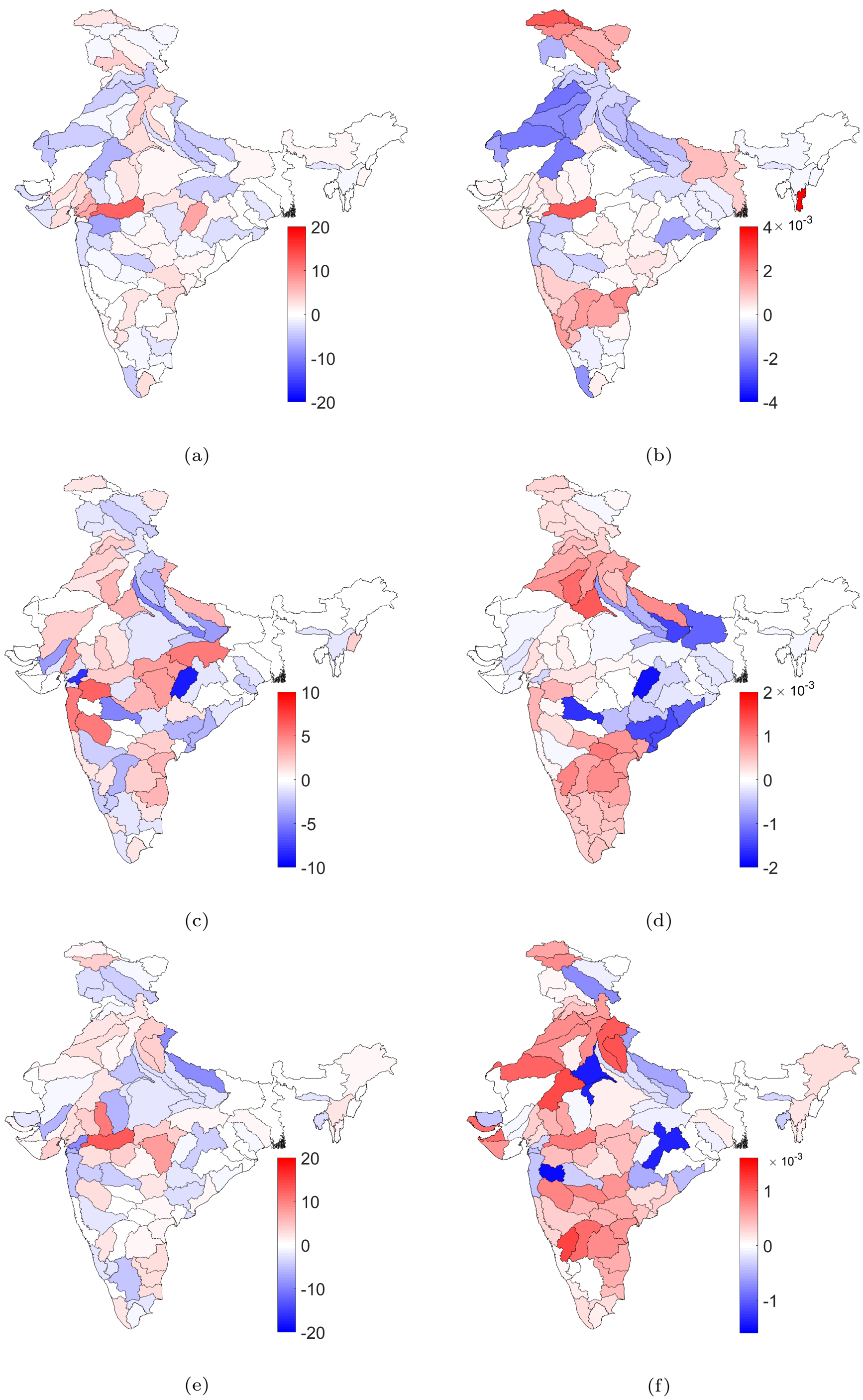

Figure 6: The degree difference(left column) and closeness difference (right column) of moderate droughts in a,b) past c,d) RCP 4.5 and e,f) RCP 8.5 scenarios are shown.

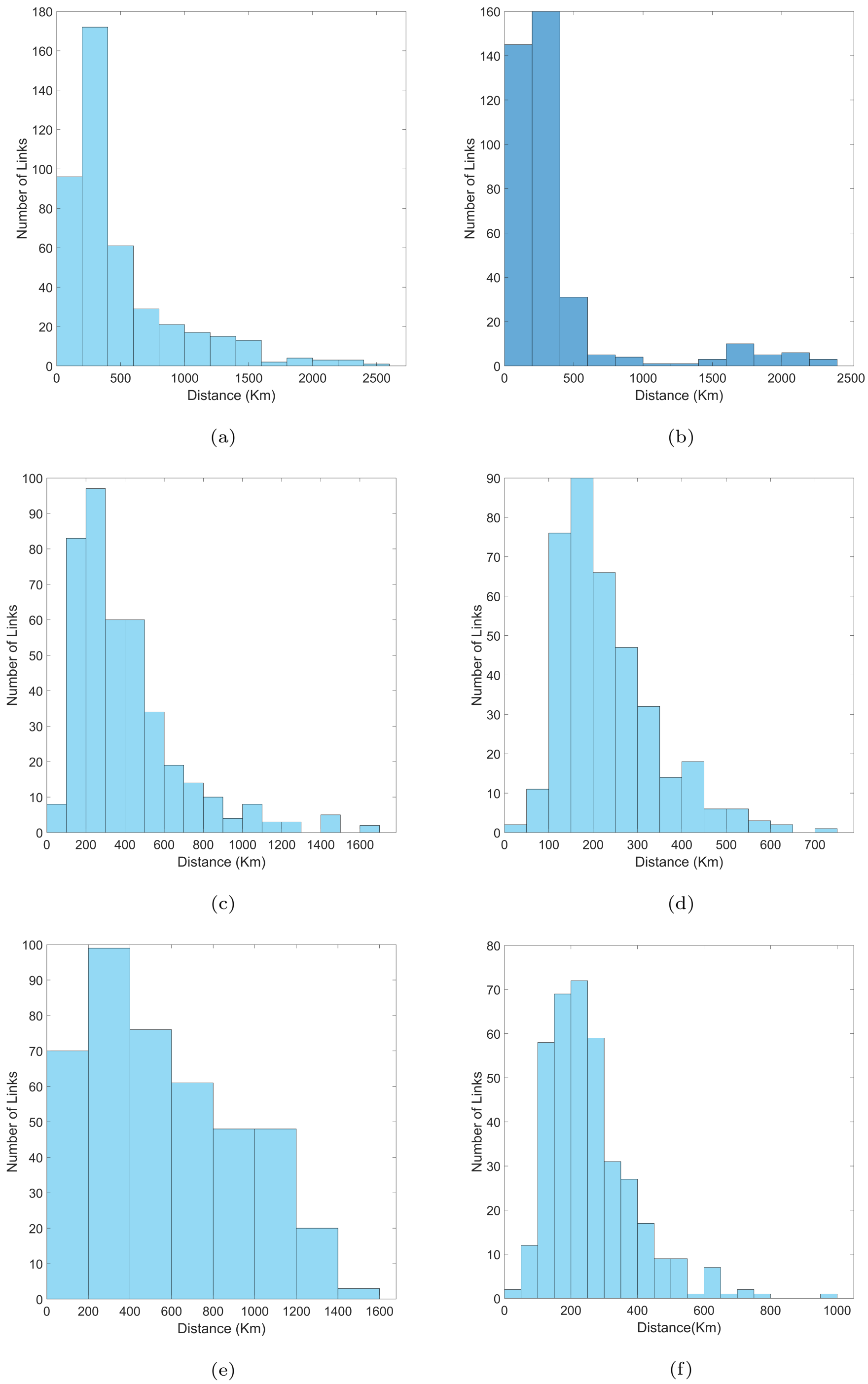

Figure 7: This figure shows the distance distribution of extreme (left column) and moderate droughts(right column) in a,b)Past c,d) RCP 4.5 e,f) RCP 8,5 scenarios