A Network Analysis of U.S. Hurricanes

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Abstract The relationships of hurricanes affecting the United States are examined using the methods of network analysis. Network analysis has been used in a variety of fields to study relational data, but has yet to be used in the study of hurricane climatology. The present work is largely expository introducing network analysis and showing one way it can be applied to understand regional hurricane activity. The network links coastal locations (termed nodes) with particular hurricanes (termed links). The topology of the network is examined using local and global metrics. Results show that certain regions of the coast (like Louisiana) have high occurrence rates, but not necessarily high values of connectivity. Regions with the highest values of connectivity include southwest Florida, northwest Florida, and North Carolina. Virginia which has a relatively low occurrence rate is well-positioned in the network having a relatively high value of betweenness. Six conditional networks are constructed based on years of below and above average values of important climate variables. Significant differences in the connectivity of the network are noted for different phases of the El Nino-Southern Oscillation.

1 Introduction

Hurricanes that make landfall in the United States pose a significant threat to life and property. The frequency and intensity of hurricanes at the coast has been studied by numerous authors (Elsner and Kara 1999; Lyons 2004; Keim et al. 2007). In fact it is well know that over the long term the United States gets hit on average by 1 or 2 hurricanes per year, with 3 of them being at Saffir Simpson category 3 or higher intensity on average every 5 years. Some studies have focused on how the frequency and intensity of coastal hurricanes change with climate (Gray et al. 1993; Lehmiller et al. 1997; Elsner and Jagger 2004; 2006). For instance, it is now well known that pre-season values of the North Atlantic oscillation (NAO) portend the risk of hurricanes reaching the United States (Elsner and Jagger 2004). Results from these studies are important for quantifying the near-term (<1 year) and longer term risk of a catastrophic hurricane loss locally.

While these studies are important in assessing the regional or local risk of a hurricane strike and how it varies with climate, they say nothing about the relationships of risk between regions or how such relationships may change with climate variations. For instance, a hurricane moving out of the Caribbean Sea may affect more than one coastal region. Over the long run this introduces correlation between the frequencies of hurricanes at different locations. Knowing which regions tend to get hit by the same hurricane can help with risk assessment especially for those selling hurricane-related insurance.

Network analysis allows us to look at hurricane landfalls in a relational way. For instance how are Florida hurricanes related to Texas hurricanes if at all. If every hurricane that strikes Florida goes on to strike North Carolina or Texas, then the risk of losses between Florida and elsewhere is correlated. This is important since companies selling insurance will want to diversify their exposure over uncorrelated regions so as to minimize the impact on their book of business from a particular event. It is our contention that interesting connections between coastal hurricane paths and climate might be available through a network analysis that have yet to be seen by more conventional approaches.

Some previous studies have considered coastal hurricanes in a relational way. Elsner and Kara (1999) examined the occurrence of hurricanes that hit both Texas and Florida in a single season. They also looked at the occurrence of hurricanes hitting both Florida and North Carolina. They found that while the frequency of Florida to North Carolina hurricanes has remained rather constant, the frequency of Florida to Texas hurricanes decreased during the second half of the 20th century. However, there was no attempt to analyze the complete network of multiple landfalls. In studying typhoons affecting China, Fogarty et al. (2006) using a factor analysis model to understand the correlated risk between coastal provinces. They found that when hurricane activity is high in the southern provinces it tends to be low in the northern provinces and that this seesaw in activity is related to the El Nino-Southern Oscillation (ENSO) phenomenon.

Network analysis offers a way to look at the correlated risk of hurricanes in a more direct and more systematic way than these previous studies. This is the first such study of its kind so in section 2 we begin with an introduction to the basic ideas behind networks. Following this, in section 3, we examine the data on U.S. landfalls providing summary statistics and plots of frequency. In section 4 we show how to construct an adjacency matrix from an incidence matrix and how the adjacency matrix leads to a network of landfalls. In section 5 we show how to compute local and global metrics associated with the topology of the network including the diameter and the prestige of individual nodes (locations). In section 6 we examine how these metrics change with climate covariates including the NAO.

2 A brief introduction to networks

Network analysis is practical application of graph theory. Graph theory is the study of mathematical structures used to model pairwise relations between objects. Networks (or graphs) have been constructed and studied for individuals, groups, transportation, or occurrences from a wide range of disciplines including computer science, biology, economics, political science, and sociology. In fact, an early application of network analysis was in the area of social interaction. Network analysis has recently been introduced into the study of climate by Tsonis et al. (2006; 2007). Because it is new to climatology and has not yet, to our knowledge, been applied to hurricanes, we begin with an introduction using concepts from social network analysis (Scott 1991, Wasserman and Faust 1994).

Consider authors publishing in the field of hurricane climatology. Authors can be represented as nodes with links to other authors established through a citation. If author A is cited by authors B and C then a network is established between the authors. The collection of authors are called vertexes or nodes and the links connecting them are called edges. Figure 1 is a hypothetical example of a social network of authors linked by citation. If author B cites author A at least once then an arrow from B to A is drawn. If two authors cite each other a double arrow is used.

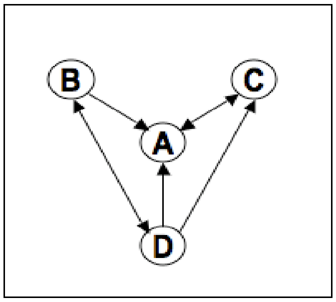

Figure 1: Hypothetical social network of authors publishing in the field of hurricane climate. The authors are represented with circles (nodes) and the links indicating at least one citation are indicated with arrows.

First note that the network is aspatial meaning that the absolute and relative positions of the nodes and links in the graph are arbitrary. What is important are the number of nodes and their linkages. Here our hypothetical network consists of 4 nodes and 5 links. The network is a concise way to examine relations. For instance the network shows that author A is cited by the other three authors so its node has the highest in-node value. While author A generates citations, he tends not to give them out. In contrast, author D is the only one that cites the other three authors so its node has the highest out-node value. Also author B does not cite author C and vice versa. But authors B and C are connected through authors A and D since B cites D who cites C and since B cites A who is cited by and cites C. This is an example of a directed graph since the links have arrows. In an undirected graph all links point both ways so no arrows are used. This is the case when the relationship between nodes is transitive. For example, if the network represents scientists who author papers and the links are co-authorships then all relations are transitive and the links do not have arrow heads.

The configuration of links among the network nodes reveals the network structure. A path connecting two nodes is a sequence of distinct nodes and links beginning with the first node and terminating with the last. For the example, above node B is connected to node C through A or through D, so that the path is BAC or BDC. If there is a path between two nodes then the nodes are said to be reachable. The length of the path is the number of links. So the length of the path from A to C is one and from B to C is two. However, another path from B to C is through A and D in which case the length is three. A shortest path between two nodes is called a geodesic. The diameter of the network is the length of the longest geodesic between all pairs of nodes in the graph. Therefore the maximum geodesic distance between any pair of nodes is the diameter. Interestingly, although the network is aspatial, many of the terms used in network analysis suggest spatial or geometric representations, including centrality, distance, isolation, and diameter.

3 U.S. hurricanes

Our interest is in constructing a network from data about hurricanes affecting the United States. First we take an exploratory look at the data that will be used in creating the network. A chronological list of all hurricanes that have affected the continental United States in the period 1851--2005, updated from Jarrell et al. (1992) is available from the U.S. National Oceanic and Atmospheric Administration (NOAA) at http://www.aoml.noaa.gov/hrd/hurdat/ushurrlist.htm. We use the May 2006 version of the data.

A hurricane is a tropical cyclone with maximum sustained (one-minute) 10 m winds of 65 kt (33 m/s) or greater. Hurricane landfall occurs when all or part of the storm's eye wall passes directly over the coast or adjacent barrier islands. Since the eye wall extends outward a radial distance of 50 km or more from the hurricane center, landfall may occur even in the case where the exact center of lowest pressure remains offshore. We also include hurricanes that do not make direct landfall, but produce hurricane force winds at the coast. A hurricane can affect more than one region as hurricanes Andrew and Katrina did in striking southeast Florida and Louisiana.

Here it is assumed that the data on hurricanes affecting the United States are complete back to 1899, but less so in the interval 1851--1898. Since we are interested in multiple strikes rather than trends over time the fact that a few hurricanes may have been missed or that a few multiple hit storms are counted only as single hits will not materially influence the network.

The record contains 275 hurricanes affecting the United States in the period 1851-2005. Regions are divided along state lines from Texas to Maine, but Texas is divided further into south, central, and north Texas and Florida is divided into four regions including northwest, southwest, southeast, and northeast Florida. This gives a total of 23 non-overlapping regions. The state two-letter abbreviation is used. South, central, and north Texas are denoted ATX, BTX, and CTX, respectively. Northwest, southwest, southeast, and northeast Florida are denoted AFL, BFL, CFL, and DFL, respectively.

Figure 2 shows the frequency of hurricanes by region. The gulf and southeast coasts from Texas to North Carolina are affected most often by hurricanes. Within this high frequency zone, Louisiana, northwest Florida, and North Carolina have the most frequent hurricanes. Within the low frequency zone, the region from New York to Massachusetts has the largest frequency. We note that within Florida, the northeast coast has the fewest hurricanes and the northwest coast has most. It should be kept in mind that the regions used in this study do not have the same area or the same coastal exposure to hurricanes so it is not advisable to make anything more than broad generalizations of hurricane frequency. The frequency of major hurricanes (category 3 or higher on the Saffir-Simpson hurricane intensity scale) shows similar results (not shown) with most activity occurring in the region from Texas to North Carolina.

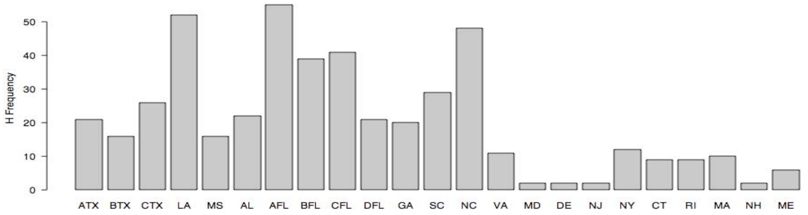

Figure 2: **Frequency of hurricanes affecting states from Texas to Maine. Texas is divided into 3 regions (south, central, and north) and Florida into four regions (northwest, southwest, southeast, and northeast).**

It is interesting to consider the time variation in hurricanes. Figure 3 shows the cumulative sum of hurricanes by year for selected regions. Hurricane rates and how they fluctuate over time can be inferred directly by examining changes in slope. We see that the rate of hurricanes affecting Louisiana is rather constant over time as indicated by a nearly straight line cumulative sum, whereas the rate of hurricanes affecting southeast Florida is variable with activity appearing in clusters

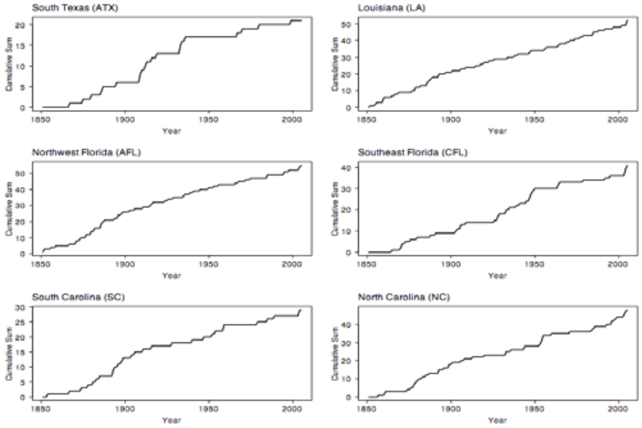

Figure 3: **Cumulative sum of hurricanes affecting selected regions along the U.S. coast**

More relevant to the present work is the occurrence of years in which two different regions are affected by hurricanes. For example, Figure 4 shows the cumulative sum of years in which both southeastern Florida and Louisiana were affect by hurricanes. Note that here the requirement is the both regions were affected in the same year, not necessarily by the same hurricane.

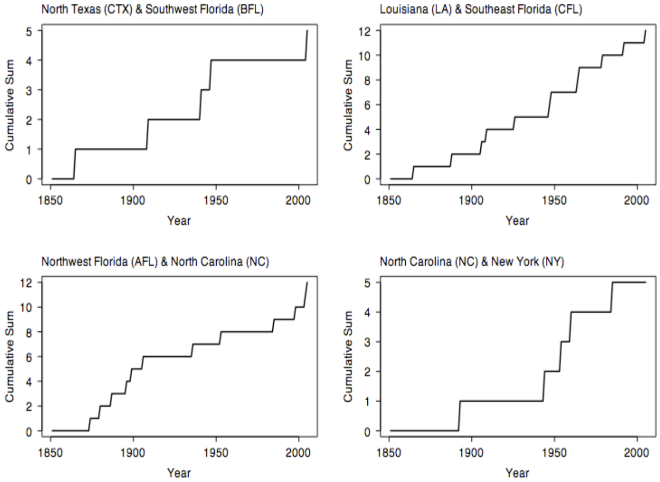

Figure 4: **Cumulative sum of years in which multiple regions where both affected by a hurricane.**

Again we see variations depending on regions. The overall rate of multiple hit years for Louisiana and southeast Florida is relative steady, whereas for northwest Florida and North Carolina the period from about 1875 through 1910 was quite active. Next we consider the relationship between regions affected by the same hurricane using the methods of network analysis.

4 A network of U.S. hurricanes

While the frequency of coastal hurricane activity is well documented, a systematic study of the relations of hurricanes affecting different regions has yet to be performed. Here we use network analysis to perform a systematic study of regional hurricane relations. As described in section 2, a network is graph connecting nodes. Here we consider a hurricane affecting a region as a node. If the hurricane affects more than one region then a link is drawn between nodes. The graph is undirected as the link between regions does not differentiate the time order of the regions affected.

4.1 Example

The network is constructed in three steps. In step 1, an incidence matrix is obtained that shows the occurrence of hurricanes by regions. In step 2 an adjacency matrix is computed from the incidence matrix using matrix algebra. In step 3, the network graph is drawn from the symmetry of the adjacency matrix. To see how this works, consider the following hypothetical table of hurricane occurrences. Hurricane 1 (H1) affected regions 1 (R1) and 3 (R3) and so on. We therefore have a 4 x 5 (hurricanes x region) incidence matrix called X. The 5 x 5 adjacency matrix A (Table 2) is computed by pre-multiplying the incidence matrix by its transpose.

	R1	R2	R3	R4	R5
H1	1	0	1	0	0
H2	1	1	0	0	1
H3	0	1	0	1	0
H4	1	0	0	0	0

Table 1: A hypothetical incidence matrix consisting of 4 hurricanes and 5 regions. Hurricane 1 affected region 1 and 3, while hurricane 4 affected only region 1.

	R1	R2	R3	R4	R5
R1	-	1	1	0	1
R2	1	-	0	1	1
R3	1	0	-	0	0
R4	0	1	0	-	-
R5	1	1	0	0	-

Table 2: **The adjacency matrix constructed from the hypothetical incidence matrix shown in Table 1. Here we see that region 1 is connected to regions 2, 3, and 5 since there was at least one hurricane to hit region 1 that went on to, or came from, these other regions. The diagonal elements of the matrix which consist of the frequency of hurricanes in each region are not used to construct the network.**

Note that the adjacency matrix is symmetric with the value in row R1 and column R2 matching the value in column R1 and row R2 and so on. The network is constructed directly from the adjacency matrix where values of 1 indicate a link between the regions. Figure 5 shows a graph of the network. Regions 1 and 2 each have three links, region 5 has two links and regions 3 and 4 each have one link. Since we do not distinguish the time order of hits, the links are undirected.

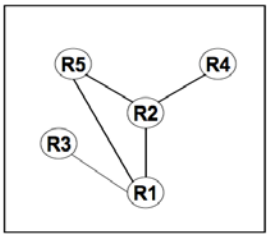

Figure 5: **Network graph based on the hypothetical set of hurricanes listed in Table 1. The network is constructed from the adjacency matrix shown in Table 2. Region 2 (R2) is connected to regions 1, 4, and 5.**

4.2 Full network

The above example explains the steps we used to construct our U.S. hurricane network. It is possible to construct other networks with the same data. Figure 6 shows the incidence matrix, adjacency matrix, and network graph for the 275 hurricanes affecting the United States during the period 1851 through 2005. The incidence matrix has 275 rows and 23 columns while the adjacency matrix has dimensions 23 by 23. The network graph is plotted directly from the adjacency matrix. All the algebra, plots, and network analysis are done using the R language (R Development Core Team (2006).

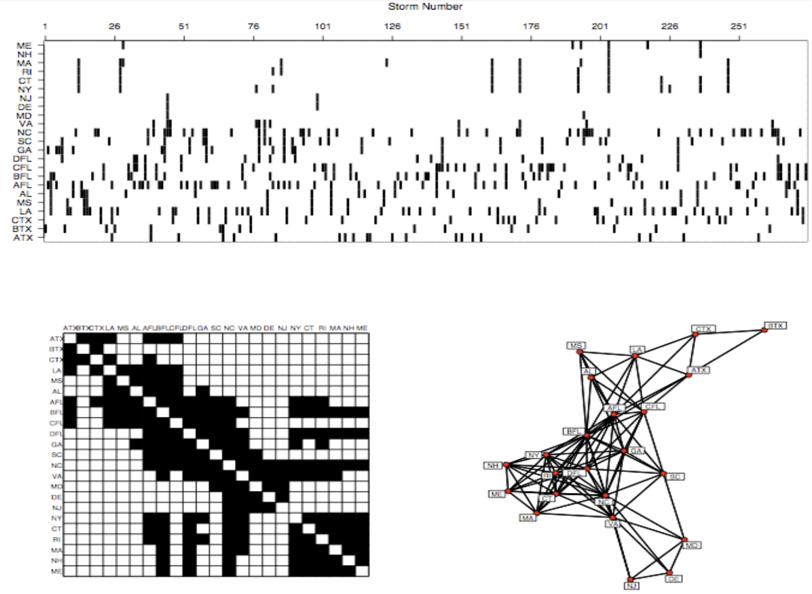

Figure 6: **Incidence, adjacency, and network of U.S. hurricanes.**

The U.S. hurricane network shows the linkages between regions affected by the same hurricane. In small coastal states or regions a single hurricane can affect more than one region as is the case in the northeast. However, hurricanes affecting Florida frequently travel on to affect other non contiguous coastal regions.

As noted above, the network can be mapped in different ways. Figure 7 shows the U.S. hurricane network mapped on a circle and on the coastline. The circle makes it easier to see the linkages resulting from traveling hurricanes. In particular we note relatively high number of links with northeastern Florida and the regions of New England

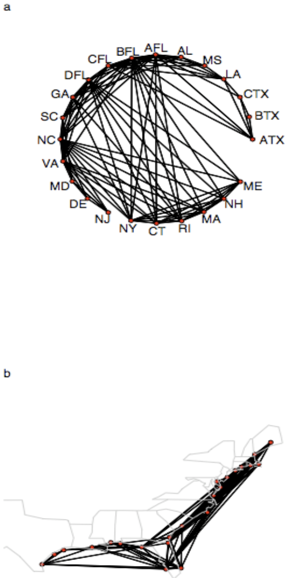

Figure 7: The U.S. hurricane network mapped on a circle (a) and on the coastal geography (b).

5 Global and local metrics of the network

Next we examine various structural properties (local and global) of the network. We use the R routines developed by Butts (2006) under the *sna* package. We consider three measures of nodal centrality. Where centrality is loosely defined as being in the "middle" of the network. Middle nodes are nodes that are connected to many other nodes in the network. They are considered structurally important to the network. The three measures we consider are degree, closeness, and betweenness.

The "degree" (prestige) of a node (vertex) is its most basic structural property, the number of links (edges) connected to it. In the hurricane network the degree of the node is the number of regions that have been affected by a hurricane affecting the particular location. Figure 8 shows a bar plot of the nodal degree. Here we see that the south Texas node has degree of 6 since it is linked to 6 other regions including central Texas, north Texas, Louisiana, northwest Florida, southwest Florida, and southeast Florida. In comparison, the central Texas node has degree 3 being linked only to south and north Texas. Nodes with the largest degree include southwest Florida and North Carolina.

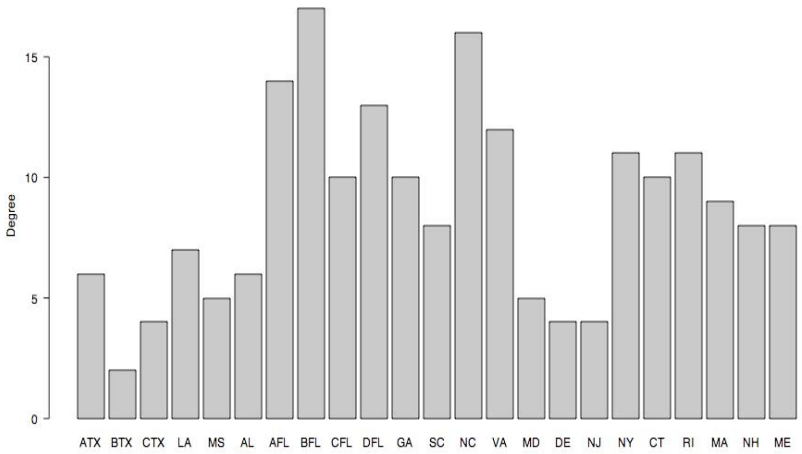

Figure 8: **Node degree. The node degree is the number of links connected to the node. Here the degree represents the number of regions affected by hurricanes that have affected the particular region. For instance, south Texas has degree 6 meaning that 6 other regions have been affected by hurricanes affecting south Texas**.

Paths through the network are the successive links between the nodes. One path from south Texas to Maine is constructed by starting in south Texas and following the link to northwest Florida. Since northwest Florida is linked to North Carolina, which is linked to Maine a path of length 3 links south Texas with Maine. The shortest path between any two nodes is called the geodesic. The shortest path between south Texas and Maine is 2 (through southwest Florida). The "closeness" of a node provides an index for the extent to which a given node has short paths to all other nodes in the graph. Mathematically it is defined as

$$C_C(v) = \frac{|V\,(G)| - 1}{\sum_{i:i \neq v} d(v, i)}$$

where d(i,j) is the geodesic distance between nodes i and j and |V(G)| is the number of nodes in the network. Figure 9 shows the closeness index by region.

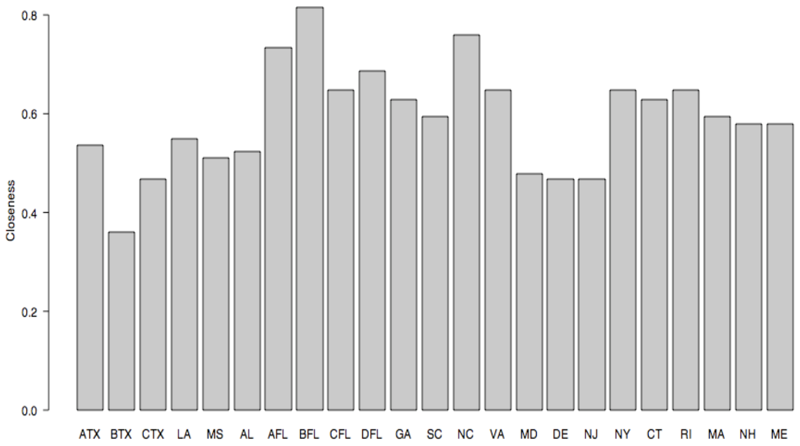

Figure 9: Node closeness. The node closeness is an index that quantifies the number of paths through the node that are geodesics.

Another important property of network nodes is called "betweenness." Betweenness is defined as the number of geodesic paths that pass through a node. It is the number of "times" that any node needs to go through a given node to reach any other node by the shortest path. Conceptually, high-betweenness nodes lie on a large number of non-redundant shortest paths between other nodes; they can thus be thought of as "bridges." A redundant path is one in which the path is traversed by more than one hurricane. Figure 10 shows the betweenness values for each of the nodes in the hurricane network.

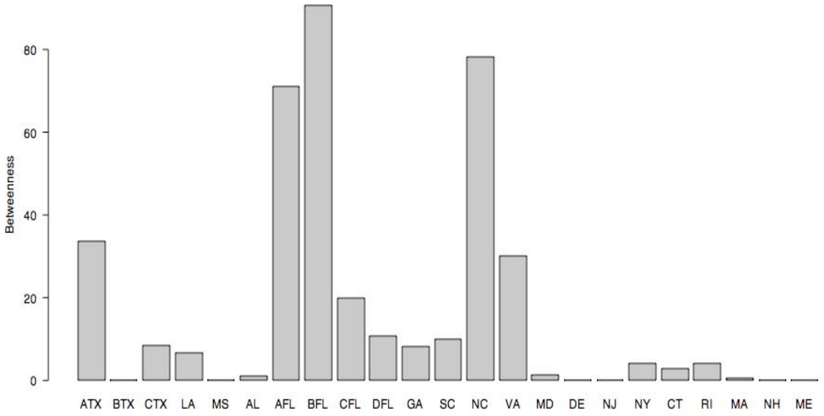

Figure 10: **Nodal betweenness.**

Global properties of the network may also be of interest. For instance, the diameter of the network can be defined as the maximum geodesic distance over the network. Here we find that this distance is 5. Thus the maximum shortest path between any two nodes is 5 links. This path connects south Texas with New Hampshire and runs through central Texas, Alabama, New York, and Rhode Island. Note that these intermediate nodes tend to have small values of betweenness.

Another global property is the clustering coefficient. Returning to our example from section 2 where we considered the citation network of hurricane researchers, two authors are adjacent in the network if they site each other's work. Consider a author with two adjacent authors, if these adjacent authors cite each other then we have a cluster or clique. The clustering coefficient of the entire network can be defined as the probability that adjacent nodes of a node are connected. The clustering coefficient for the U.S. hurricane network is 0.46 indicating that slightly less than half of all regions that are linked to a specific region are also linked together.

6 Conditional networks

It is interesting to consider how the hurricane network properties change with climate factors. Here we consider three variables that have been related to U.S. hurricane activity. The variables include an index of the North Atlantic Oscillation (NAO), an index of the El Nino-Southern Oscillation (ENSO), and North Atlantic ocean temperatures (SST). Ordered factors are created by consider whether a year is above or below the long term average based on seasonal averages of the variables. Six separate networks are constructed using only hurricanes from years that fall into the six factor groups.

NAO index values are calculated from sea level pressures at Gibraltar and at a station over southwest Iceland (Jones et al. 1997), and are obtained from the Climatic Research Unit. The values used here are an average over the pre- and early-hurricane season months of May and June and are available back to 1851. Units are standard deviations. These months are chosen as a compromise between signal strength and timing relative to the hurricane season. The signal-to-noise ratio in the NAO is largest during the boreal winter and spring (see Elsner et al. 2001), whereas the Atlantic hurricane season begins in June.

Values of the Southern Oscillation Index (SOI) are used as an indicator of ENSO. Although noisier than equatorial Pacific SSTs, values are available back to 1866. The SOI is defined as the normalized sea-level pressure difference between Tahiti and Darwin. The SOI is strongly anti-correlated with equatorial SSTs so that an El Nino warming event is associated with a negative SOI. Units are standard deviations. The relationship between ENSO and hurricane activity is strongest during the hurricane season, so we use an August through October average of the SOI for our covariate. The monthly SOI values are obtained from the Climatic Research Unit where they are calculated based on a method given in Ropelewski and Jones (1987).

The SST values are based on a blend of model values and interpolated observations, which are used to compute Atlantic SST anomalies north of the equator (Enfield et al. 2001). As with the SOI, we use a August through October average of the SST anomalies as our covariate. The anomalies are computed by month using the climatological time period 1951–2000 and are available back to 1871. Units are degrees C. Values are obtained online from NOAA-CIRES Climate Diagnostics Center (CDC).

Table 3 summarizes the network properties conditional on each of the factors. We see that the hurricane network changes substantially between above and below phases of the ENSO. With below average values of the SOI characteristic of an El Nino event in the tropical Pacific, the mean nodal connectivity is 4.8+/-0.79. This value is significantly less than the value of 7.2+/-0.98 for the La Nina network of U.S. hurricanes. We also see more connectivity during warm SST years compared with cool SST years. The mean betweenness value during below average NAO years is higher largely due to the fact that North Carolina has a betweenness value of 251 compared with 9 during above average NAO years. The largest betweenness value during above average NAO years is 141 for southwest Florida. The connectedness which measures the fraction of all possible links over all nodes is highest for the below normal NAO and above normal SST and smallest for the below normal SOI.

	NAO Above	**NAO Below**	**SOI Above**	**SOI Below**	**SST Above**	**SST Below**
Max Degree	16	16	16	11	16	14
Mean Degree	6.5+/-0.95	6.4+/-0.63	7.2+/-0.98	4.8+/-0.79	7.1+/-0.86	5.6+/-0.67
Max Betweenness	141 (BFL)	251 (NC)	94 (BFL)	73 (LA)	110 (NC)	134 (AFL)
Mean Betweenness	12.8+/-6.4	22.3+/-11.7	10.9+/-4.4	13.3+/-4.6	16.5+/-6.6	14.5+/-6.0
Connectedness	0.75	1.00	0.75	0.60	0.91	0.75

Table 3: **Network properties conditional on climate factors**.

7 Summary

Hurricane activity can have profound affects on lives and property along the coast. The frequency and intensity of hurricanes is the topic of much of the current research. Much less work has been done to understand the relationship of hurricanes across different regions. Here we examined the data on hurricanes that have affected the U.S. coast from a relational perspective using network theory. The tone of the chapter is expository since the analysis of climate data using networks is relatively new. In fact, the basics of networks are introduced using a hypothetical network of citations in the hurricane climate literature.

The primary analysis centers on the network of U.S. hurricanes. The network is created by considering hurricanes that have affected more than one coastal region. The regions are based on individual States, but Texas and Florida are further subdivided. The chapter describes how the adjacency matrix is derived from the incidence matrix and how a network is a graphical representation of the adjacency matrix. Graphical representations can be done in various ways to highlight different characteristics of the network.

The topology of the network is examined using various local and global metrics including degree, closeness, betweenness, diameter, and clustering coefficient. The degree quantifies the number of links between each node where a link between two nodes is established if at least one hurricane affected both regions. Areas that are affected by hurricanes making multiple landfalls have high degree. Paths through the network are routes between nodes via the links. Closeness and betweenness quantify how many shortest paths go through each node. The diameter and clustering coefficient are global metrics and measure the maximum shortest path in the network and the probability that adjacent nodes are linked, respectively.

The question of how the topology changes with changing climate is considered by reconstructing networks based on three independent climate factors. It is found that the ENSO phenomenon in the equatorial Pacific has the most significant influence on the network. The present work represents a first step toward understanding relational aspects of hurricane activity using networks and how those relationships change under different climate scenarios. The next step is build prediction models of network structure based on pre-season climate conditions.

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