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NETWORK ANALYSIS OF HURRICANES AFFECTING THE UNITED STATES

By

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This dissertation is dedicated to all people that had the faith in me to know that I would eventually reach my goal. Dr. Elsner thank you for your support, advise and guidance. To all of my friends and family thank you for hanging in there with me all these years! Mom thank you for giving me a place when I had nothing left. Liz I could not have done this without your library access. Jody thanks for always listening and giving me your honest opinion, you are like the older sister I never had. Kevin and Evan you are the two people in my life that have always provided me with continual peace of mind, thank you. Lucinda and Heather, thank you for having many children so I did not have to. John thank you for your love and support. Dad I wish you were here to see this.

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ABSTRACT

Hurricanes affecting the United States cause severe damage and kill people. The risk of future hurricane activity along the coast is the subject of much scientific and public interest. While considerable work had been done to understand the occurrence of hurricanes along the coast, much less has been done to examine the inter–relationships among the hurricanes. This dissertation concerns the relationships of hurricanes affecting the United States using 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 how it can be applied to possibly better understanding regional hurricane activity as well as hurricane activity overtime.

The research is divided into two cases. The first case consists of networks developed based on the relationships of spatial locations of landfalls and the second part consists of networks developed based on the relationships of the temporal occurrence of landfalls. In the first case, 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 hurricane occurrence rates, but not necessarily high values of network connectivity. Low values of connectivity indicate that hurricanes affecting Louisiana tend not to affect other regions. 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. In the second case, the year-to-year variation in U.S. hurricane activity is examined by extending the ideas and concepts of network analysis for time series data. The "visibility" network link years experiencing a hurricane landfall with

other hurricane landfall years “visible” to each other through time. The topology of the visibility network is examined using local and global metrics. Results show that overall the visibility network has few years with many lines of visibility, therefore, many linkages to other years. Years with high hurricane count have more visibility in the network than those years that have less storms. Among years with high counts the years that are surrounded (before and after) with years of low counts will have greater visibility. The years 1886, 1893, 1955 and 2004 are highly visible in the network of U.S. hurricanes. A year is more central if it is a link in more visibility chains between other years in the network.

Six conditional networks are constructed for the spatial and temporal networks 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 Niño-Southern Oscillation. During El Niño years, when the equatorial waters of the eastern Pacific are warm, there tends to be shearing winds and subsidence over large portions of the North Atlantic where hurricanes form. These conditions lead to fewer hurricanes affecting the United States. More work is needed to better understand the details of how climate influences the network of landfalls.

The scientific merit of the research is a better understanding of the relationships in the regional risk of hurricane activity. The broader impacts are an introduction of network analysis to hurricane climatology.

CHAPTER 1

INTRODUCTION

Hurricanes that make landfall pose a significant threat to life and property because of the attendant surge of water and strong winds. Property damage in the United States averages in the billions of dollars annually (Pielke et al. 2008) and it anticipated that a strong hurricane directly affecting Miami or New York could cause in excess of $100 billion in total damage. While tropical cyclones occur over the warm tropical waters of the North Atlantic ocean, North Pacific ocean, Indian ocean, and South Pacific ocean, this dissertation concerns hurricanes (strong tropical cyclones) that occur over the North Atlantic and affect the United States.

A hurricane begins as an area of low air pressure over warm ocean waters (at least 27 degrees Centigrade down to 50 meters below the sea surface). As a result of atmospheric instability, the area of low pressure features numerous showers and thunderstorms that, over several days, organize the winds into a counterclockwise (clockwise in the Southern Hemisphere) swirl. The swirl in turn organizes the existing thunderstorms and helps new thunderstorms develop. The swirl then becomes a tropical storm when the circulating wind speeds, estimated at 10 meters above the ocean, exceed 17 meters per second (averaged over a one-minute time interval).

When the wind speeds reach 64 kt or more the tropical storm is called a hurricane. Once formed, the hurricane winds are maintained by the import of heat from the ocean at high temperature and the export of heat at lower temperature in the upper troposphere (near 16 kilometers) similar to the way a steam engine converts thermal energy to mechanical motion. On average 50 hurricanes occur worldwide each year. Hurricanes develop during the time of the year when the ocean temperatures are hottest. Over the North Atlantic (including the Gulf of Mexico and Caribbean Sea) this includes the months of June through

November with a sharp peak from late August through the middle of September when sea surface temperature is at a peak (Elsner and Kara 1999).

Hurricanes are steered by large-scale wind streams in the atmosphere above the surface and by the increasing component of the Earth's spin away from the equator. In the deep tropics these forces push a hurricane slightly north of due west (in the Northern Hemisphere). Once north of about 23 degrees of latitude a hurricane tends to take a more northwestward track then eventually northeastward at still higher latitudes. This creates the parabolic shaped track often observed on maps of historical hurricanes (Elsner and Kara 1999). Local fluctuations in the magnitude and direction of steering can result in tracks that deviate significantly from this pattern.

Landfall occurs when the hurricane center crosses a coastline. Because the fastest winds are located in the eyewall it is possible for a hurricane's fastest winds to be over land even if landfall does not occur. Similarly it is possible for a hurricane to make landfall and have its fastest winds remain out at sea. Fortunately, for life and property, the winds slacken quickly after the hurricane moves over land. Hurricanes made landfall in the United States at an average rate of five every three years during the 20th century (Elsner and Kara 1999).

The frequency and intensity of hurricanes at the coast have 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 (see chapter 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) and that El Niño conditions tend to lessen the probability of a hurricane affecting the United States (Bove et al. 1998). 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 and over time 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 of the United States. 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.

This dissertation will adopt the methods of network analysis to examine hurricanes affecting the Untied States. Network analysis allows one 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 anticipated 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 in their study to analyze the complete network of multiple landfalls. In studying typhoons affecting China, Fogarty et al. (2006) used 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 Niño-Southern Oscillation (ENSO) phenomenon. ENSO is a coupled ocean-atmosphere subsystem of the climate system that features changes in winds and ocean temperatures across the equatorial Pacific Ocean.

This dissertation will be the first systematic attempt to understand U.S. hurricane climatology from the perspective of network theory. First, a network of hurricane landfalls will be created by considering hurricanes that have affected more than one coastal region. The regions will be individual states, but Texas and Florida will be further subdivided. The goal is to use methods from network analysis to examine geographic relationships (linkages) between coastal hurricanes affected the United States. Importantly the work will determine if these linkages change under climate changes measured by large-scale variables, such ENSO. Second, a network of hurricane years will be created by considering years with hurricane counts that are "visible" from other years.

The research will attempt to answer the following questions:

1. How can the occurrence of U.S. hurricane landfalls be examined from the perspective of network analysis? What advantages are gained from this perspective?

2. What relationships as defined by the network exist between landfall locations, especially locations separated by distance?

3. How are these relationships affected by large scale climate variations, such as ENSO?

The intellectual merit of the proposed work will be advances in understanding historical coastal hurricane activity and the broader impacts will a new toolkit for analysis and modeling in the climate sciences.

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. Since this is the first such study of its kind Chapter 2 begins with an introduction to the basic ideas behind networks. Following this, Chapter 3 covers the examination of the data on U.S. landfalls providing summary statistics and plots of hurricane frequency. Part one begins in Chapter 4 with a discussion on spatial networks of hurricane affecting the United States. It details how to construct an adjacency matrix from an incidence matrix and how the adjacency matrix leads to a network of landfalls. In Chapter 5 it is demonstrated how to compute local and global metrics associated with the topology of the network including the diameter and the degree of individual nodes (locations). In Chapter 6 how these metrics change with climate covariates including the North Atlantic oscillation (NAO) is examined. Part two starts in Chapter 7 and outlines a temporal network of hurricane affecting the United States. A visibility network is created for the years 1851–2008 and subsequent network properties are examined and compared across three broad regions. Six separate visibility networks are constructed and are compared using large scale climate covariates. The dissertation concludes with a summary and discussion of future areas of research.

CHAPTER 2

AN INTRODUCTION TO NETWORK ANALYSIS

Chapter one provided a motivation for the problem and the approach taken in this dissertation. This dissertation research depends on the application of network analysis. This chapter provides some background material on this approach.

Network analysis is the practical application of graph theory. Graph theory is the study of mathematical structures used to model pairwise relations between objects. A network is a graph together with a function which maps the edge set into the set of real numbers (Chartrand 1985). The study of networks has a long history in mathematics and the sciences. Leonhard Euler's celebrated 1735 solution of the Königsberg bridge problem (see Figure 2.1) is often cited as the first true proof in the theory of networks, and during the twentieth century graph theory has developed into a substantial body of knowledge (Newman 2003).

The classic model of a network, known of as the *random graph* was first described by Russian mathematician and biologist Anatol Rapoport in the early 1950's. Before being rediscovered and analyzed by Paul Erdős and Alfréd Rényi in a series of papers in the late 1950's and early 1960's, introducing probabilistic methods in graph theory. During that same time period a social scientist and mathematician, Ithiel de Dola Pool and Manfred Kocken, respectively discussed the concept of "small-world effect." The small world phenomenon is sometimes also known as "six degrees of separation" since, in the social network of the world, any person turns out to be linked to any other person by roughly six connections (Barabási 2003). Networks, historically, have been studied extensively in the social sciences (Newman et al. 2006).

Recent years, have witnessed a substantial new movement in network research, with the focus shifting away from the analysis of single small graphs and the properties of individual nodes or edges within such graphs to consideration of large-scale statistical properties of

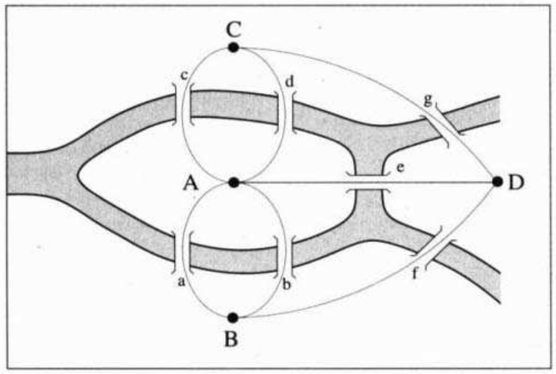

Figure 2.1: Königsberg bridge. The layout of Königsberg before 1875, with Kneiohof island (A) and the land area D caught between the two branches of the Pregel River. Solving the Königsberg problem meant finding a route around the city that world require a person to cross each bridge only once. In 1736, Leonhard Euler gave birth to graph theory by replacing each of the four land area with nodes (A to D) and each bridge with a link (a to g), obtaining a graph with four nodes and seven links. He then proved that on the Königsberg graph, a route crossing each link only once does not exit (Barabási 2003). Image borrowed from *Linked* by Albert–László Barabási

graphs. This new approach has been driven largely by the availability of computers and communication networks that allow us to gather and analyze data on a scale far larger than previously possible (Newman 2003). Modern 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. The research conducted here on the network of U.S. hurricanes is more traditional in that it focuses on relatively small graphs.

A network is modeled as a graph G which consists of a set V of nodes and a set E of edges, which are regarded as un-ordered pairs of distinct nodes (Wuchty and Stadler 2003). Networks provide the tool to consider relationships between individuals, objects or events.

Those relationships may be those of friendship, dominance, communications and so on. By a *relation* R on a set V, we mean any subset of $V \times V$. Thus, if $|V| = n$ for some finite set V, then a relation on V may have as many as n^2 elements, or as few as zero elements. We say that a is related to b by R because $(a, b) \in R$ (Chartrand 1985). The relations may be one-directional (directed) or mutual (undirected), and they may be characterized by different levels of intensity or involvement. These differences in the content and form of the relationship help define the kind of analysis performed. Additionally, the analysis may be done at several levels, concentrating on individuals and their relationships with specific other individuals or, at the highest level, on the complete network or system of relationships (Knoke and Kuklinski 1982).

Mathematically, in a graph G, we refer to V as the vertex set, each element of V being called a vertex (node). The line connecting two vertices, also know as a link or edge. Each element E. That is, each set consisting of two symmetric ordered pairs from R (relation), is called an edge, and E itself is called the edge set of G. The number of edges in G is called the size of G. Hence $|V| =$ *order* of G and $|E| =$ *size* of G (Chartrand 1985). The fundamental unit of a network is the node (vertex). The nodes in a network can be many things. For example, in a network of scientists, the nodes are scientists that are connected (linked by an edge) to other scientists with whom they collaborated. A network is considered a system of interacting nodes. In a simple undirected network, the degree of the node is equal to the number of nodes that are adjacent to this node. Adjacency is the graph theoretical expression of the fact that two agents represented by points (nodes) are directly related or connected with one another. Those nodes to which a particular node is adjacent are termed its neighborhood, and the total number of other nodes in it's neighborhood is termed its degree (strictly, it's degree of connection). Hence, the degree of a node is a numerical measure of the size of its neighborhood (Scott 1991).

There are four basic types of networks: regular (ordered) networks, classical random networks, small-world networks, and networks with a given degree distribution. Regular (ordered) networks have a fixed number of nodes, with each node having the same number of links connecting it in a specific way to a number of neighboring nodes. In this type of network if each node is linked to all other nodes in the network, this would be considered a 'fully connected' network. Regular networks are locally clustered, meaning that it takes many steps to go from one node to another node away from it is immediate neighborhood.

Therefore, unless fully connected regular networks do not efficiently transfer information within the network. Classical random network nodes are connected at random. Random networks do not exhibit local clustering, faraway nodes can be connected just as easily as nearby nodes. Thereby efficiently transferring information within the network. Small world networks (Watts and Strogatz 1998), exhibit high degree of local clustering, like that of a regular (ordered) network, yet contain a small number of long-range connections, thereby making them as efficient in transferring information as a random network. The degree distribution is a characterization function used in the analysis of networks. In real world situations networks come in a variety of distributions such as truncated power-law distributions, Gaussian distributions, power–law distributions, and distributions consisting of two power laws separated by a cutoff value (Tsonis et al. 2008; Strogatz 2001). The most common degree distribution network is the scale–free network. This network has properties similar to that of a small world network, but this similarity is achieved not by local clustering and a few random connections. It is attained by having a few elements with large numbers of links and many elements having very few links (Tsonis et al. 2008). Whatever the type of network, its underlying topology provides clues about the collective dynamics of the network (Tsonis and Roebber 2003).

Network analysis has recently been introduced into the study of climate by Tsonis et al. (2006; 2007). They use weather data collected over the global and assimilated to a grid. The pairwise correlation in geopotential heights between each grid point are computed and a correlation above a specified threshold defines whether two grid points (nodes) are connected. They find that middle-latitude weather is characterized by a few geographic locations having links as opposed to the tropic where most locations have about the same number of links.

2.1 Example

Since network analysis is relatively new to climatology and has not yet, to my knowledge, been applied to hurricanes, this section begins 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

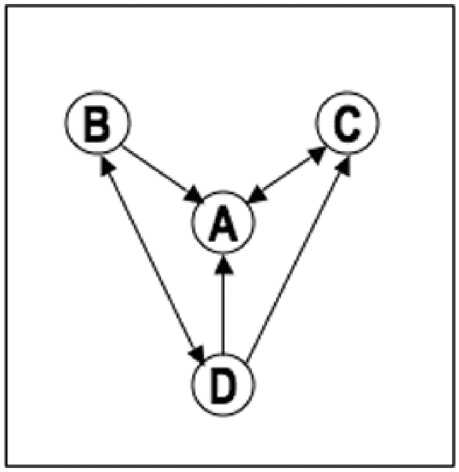

Figure 2.2: Hypothetical network of authors publishing in the field of hurricane climate. The authors are represented with circles (nodes) and the links indicating at least one citation are indicated with arrows.

edges. Figure 2.2 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.

First note that the network is aspatial meaning that the absolute and relative positions of the nodes and links displayed in the graph are arbitrary. Thus space gets defined through the topology of the network. What is important are the number of nodes and their linkages. Here the hypothetical network consists of 4 nodes and 5 links. The network is a concise way to examine relationships. 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. A relation R on set V is called *transitive* if whenever $(x, y) \in R$ and $(y, z) \in R$, then $(x, z) \in R$ (Chartrand 1985). 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 networks used in this dissertation are undirected although it would be possible to redefine the linkages and produce directed graphs.

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 a path is measured by the number of lines (edges) that make it up. 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.

The term "geodesic" comes from geodesy, the science of measuring the size and shape of Earth; in the original sense, a geodesic was the shortest route between two points on the Earth's surface, namely, a segment of a great circle. The term has been generalized to include measurements in much more general mathematical spaces; for example, in graph theory we consider a geodesic between two nodes of a graph. For the present work a geodesic path is the shortest path through the network from one node to another. Keep in mind there may be more that one geodesic path between two nodes.

The diameter of a network is the length of the longest geodesic path between any two nodes. The path length is defined as the number of links (edges) along the geodesic. Therefore the maximum geodesic distance between any pair of nodes is considered the diameter of the network. 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.

Network analysis is the focus of this dissertation. This chapter has provided an introduction to network analysis including a brief history and some formal definitions. Network analysis will be applied to data sets chronicling hurricanes affecting the United States over the past century and a half. The next chapter describes the hurricane and related data that are used in this research.

CHAPTER 3

HURRICANES AFFECTING THE UNITED STATES

The previous chapter introduced the concept and terms of network analysis. This chapter describes the hurricane data used in the dissertation to construct the networks and provides an exploratory look at these data. The primary interest is to construct networks from data about hurricanes affecting the United States. Reliable records of hurricanes along the U.S. coastline extend back more than 100 years and for fairly obvious reasons there is significant interest in understanding climatological aspects of coastal hurricane activity.

3.1 Data and source

A chronological list of all hurricanes that have affected the continental United States in the period 1851–2008, updated from Jarrell et al. (1992) is available from the U.S. National Oceanic and Atmospheric Administration (NOAA) at the following website address: `http://www.aoml.noaa.gov/hrd/hurdat/ushurrlist.htm`. The National Hurricane Center (NHC) maintains a computer file online at the following website address: `http://www.nhc.noaa.gov/tracks1851to2007_atl_reanal.txt`. This data set contains information pertaining to North Atlantic tropical cyclones. This file better know as the best track or HURDAT, contains dates, tracks, wind speeds, and central pressure values (if available) for all tropical cyclones occurring over the last 158-year period, 1851 through 2007 and is updated annually. The Jarrell et al. (1992) "list" (shown in Appendix A) was updated for this dissertation to include storms through 2008 using information from the NHC tropical cyclone reports.

Moreover, since the official list has not been updated since May 2006 it was discovered that some storms were not included, other storms have been updated as affecting more areas, in addition to changes in the category of some storms. The inclusion of an "I" in front of regions affected is added to the list, as this designation indicates a inland affected area, therefore are included in the data set. The first storm in the year 1852 on the list is not used as there is no record of it in the best track. Additionally, there are two entries that are not included because the winds affecting the U.S. were not at hurricane strength, these are the third storm in 1888 and the first storm in 1908.

Technically a hurricane is a tropical cyclone with maximum sustained (one-minute) 10 meter 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. The eye wall is the ring of strong winds and heavy rain surrounding the hurricane's nearly calm center (eye). The strongest winds of the hurricane are typically found in the eyewall. In fact, the most dangerous and destructive part of a tropical cyclone is the eye wall. Here winds are strongest, rainfall is heaviest, and deep convective clouds rise from close to a height of 15,000 meters (49,000 feet) or more above the ocean.

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. Also included are 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. Indeed, this aspect of hurricane landfalls is the major focus of the dissertation.

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 the interest is 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 results presented in this dissertation.

The record contains 283 hurricanes affecting the United States in the period 1851–2008. 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. The cutoff locations between the three Texas regions include Corpus Christi and Matagorda Bay. Northwest, southwest, southeast, and northeast Florida are denoted AFL, BFL, CFL, and DFL, respectively. The cutoff locations between the four

Florida regions include Tarpon Springs, Key Largo, and Cape Canaveral.

Besides the hurricane data, this dissertation makes use of several climate variables and indices. The main climate variable of interest is the temperatures of the ocean over which hurricanes that affect the United States are born. A tropical cyclone derives its energy from the warm ocean so it stands to reason that all other factors being equal, the warmer the ocean the stronger the cyclone. Note here that although the concern is the frequency of hurricanes, the strength of the tropical cyclone plays a role as hurricanes are defined as tropical cyclones above the threshold intensity of 64 kt. Records of sea-surface temperature (SST) averaged over the basin during the hurricane season are used in this study. Two other climate indices are important. They include the Southern Oscillation Index (SOI) and the North Atlantic oscillation (NAO). The SOI measures the changes associated with El Niño and the NAO measures the variability in tracks of middle-latitude storms across the northern part of the North Atlantic. Descriptions of these climate variables and their sources are provided in Chapter 6.

3.2 Exploratory analysis

Prior to using the U.S. hurricane data to construct networks, some exploratory plots of the data are constructed and examined. Figure 3.1 shows the frequency of hurricanes by region. The Gulf and southeast coasts from Texas to North Carolina are affected most often by hurricanes that hit the United States. 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 have the largest frequency. Note that within Florida, the northeast coast has the fewest hurricanes and the northwest coast has most.

The mean hurricane rate for each region is shown in Table 3.1. The mean rate is computed by dividing the total number of hurricanes by the number of years. Northwest Florida, Louisiana, and North Carolina are the top of the list for average hurricane occurrences. Whereas, places in the Northeast such as Maryland, Delaware and New Jersey have many fewer hurricanes on average. 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)

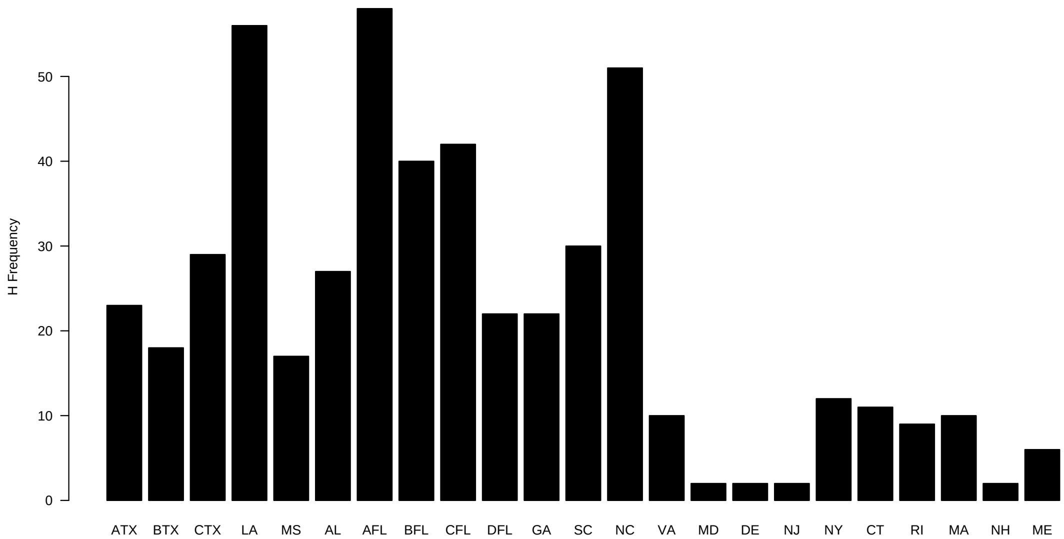

Figure 3.1: Frequency of hurricanes affecting states from Texas to Maine. The frequency is the number of hurricanes affecting the region over the period 1851-2008. Texas is divided into 3 regions (south, central, and north) and Florida into 4 regions (northwest, southwest, southeast, and northeast). The states are listed in their geographic order from Texas through Maine. There are many more hurricanes from North Carolina southward.

shows similar results (not shown) with most activity occurring in the region from Texas to North Carolina.

The Saffir-Simpson scale divides hurricanes by their intensity as measured by their maximum near-surface (10 m) wind speed using 1-minute averages. The scale is used to give an estimate of the potential property damage and flooding expected along the coast from a hurricane landfall. Wind speed is the determining factor in the scale. On the Saffir-Simpson scale a category 1 hurricane corresponds to winds of 64-82 kt (74-95 mph). Damage from category one hurricane winds occur to unanchored structures, shrubbery and poorly constructed signs. A category 2 hurricane corresponds to winds of 83–95 kt (96-110 mph). Damage from category two winds include roofs and windows in some buildings and some trees blown down. Considerable damage to mobile homes and piers are common. A category 3 hurricane corresponds to winds of 96–113 kt (111–130 mph). Damage is extensive to trees and and shrubs with large trees sometimes blown down. Mobile homes and poorly constructed

Table 3.1: Average rate of hurricane landfalls for each region from 1851 - 2008. The regions with the highest average hurricane occurrences include: northwest Florida, Louisiana, North Carolina, southeast Florida and southwest Florida.

Region	Rate
ATX	0.145
BTX	0.113
CTX	0.183
LA	0.354
MS	0.107
AL	0.170
AFL	0.367
BFL	0.253
CFL	0.265
DFL	0.139
GA	0.139
SC	0.189
NC	0.322
VA	0.063
MD	0.012
DE	0.012
NJ	0.012
NY	0.075
CT	0.069
RI	0.056
MA	0.063
NH	0.012
ME	0.037

signs are destroyed. A category 4 hurricane corresponds to winds of 114–135 kt (131–155 mph). With winds of category 4 structural damage to residential and utility buildings is common and curtain wall failures are likely. Roof structures may fail with extensive damage to doors and windows. A category 5 hurricane corresponds to winds in excess of 135 kt (155 mph). With these winds complete roof failure occurs on many homes and industry buildings with extensive window and door damage. Mobile homes are completely destroyed.

For this work it is interesting to consider the time variation in hurricanes. Figure 3.2 shows the cumulative sum (cumulative distribution) of hurricanes by year for selected regions. Hurricane rates and how they fluctuate over time can be inferred directly by examining

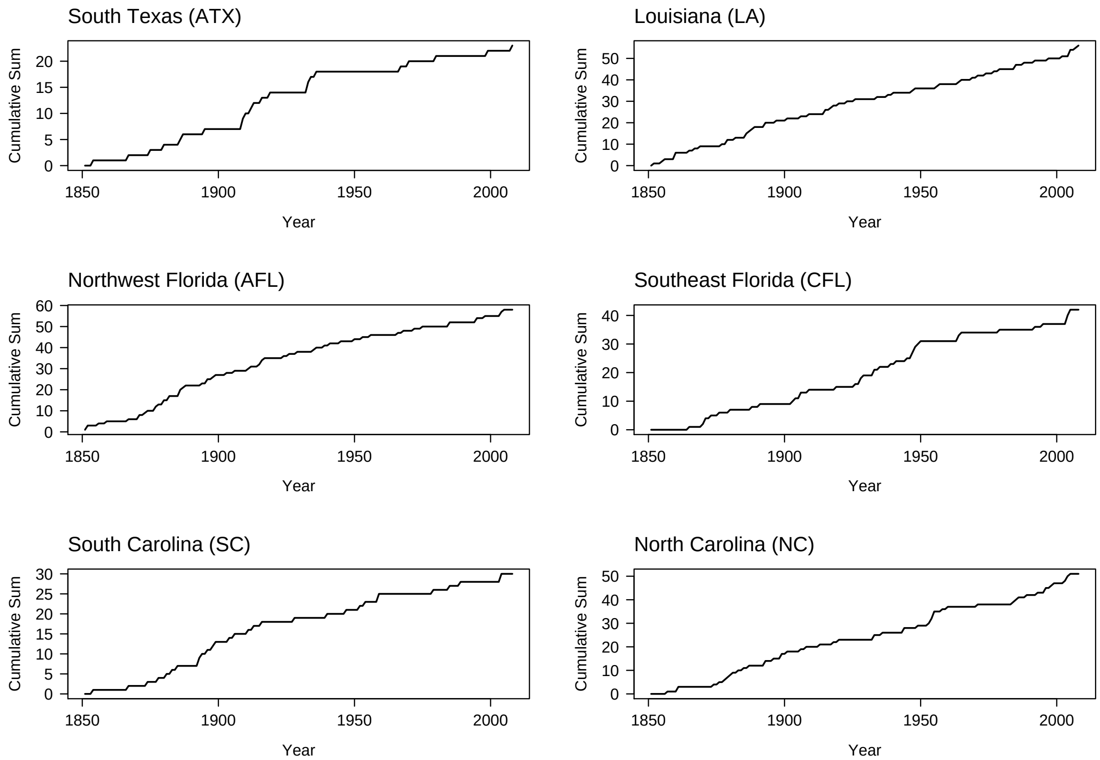

Figure 3.2: Cumulative sum of hurricanes affecting selected regions along the U.S. coast. The plot is created by summing the occurrence of a hurricane in the region as the years advance. Each "step" on the plot indicates at least one new hurricane occurrence. The overall rate (average number per year) can be inferred by the slope of the curve. Note the large variation from a straight-line slope for southeast Florida compared to Louisiana.

changes in the slope of the curves. For instance, the rate of hurricanes affecting Louisiana (average number per year) is rather constant over time as indicated by a nearly straight line cumulative sum, whereas in comparison the rate of hurricanes affecting southeast Florida is quite variable with activity appearing and disappearing in clusters. This difference in the way hurricanes occurrence fluctuate around the mean rate can have important implications for risk management (Elsner and Kara 1999).

More relevant is the occurrence of years in which two different regions are affected by hurricanes. For example, Figure 3.3 shows the cumulative sum of years in which both southeastern Florida and Louisiana were affect by hurricanes. Note here the requirement is that both regions are affected in the same year, not necessarily by the same hurricane. Thus

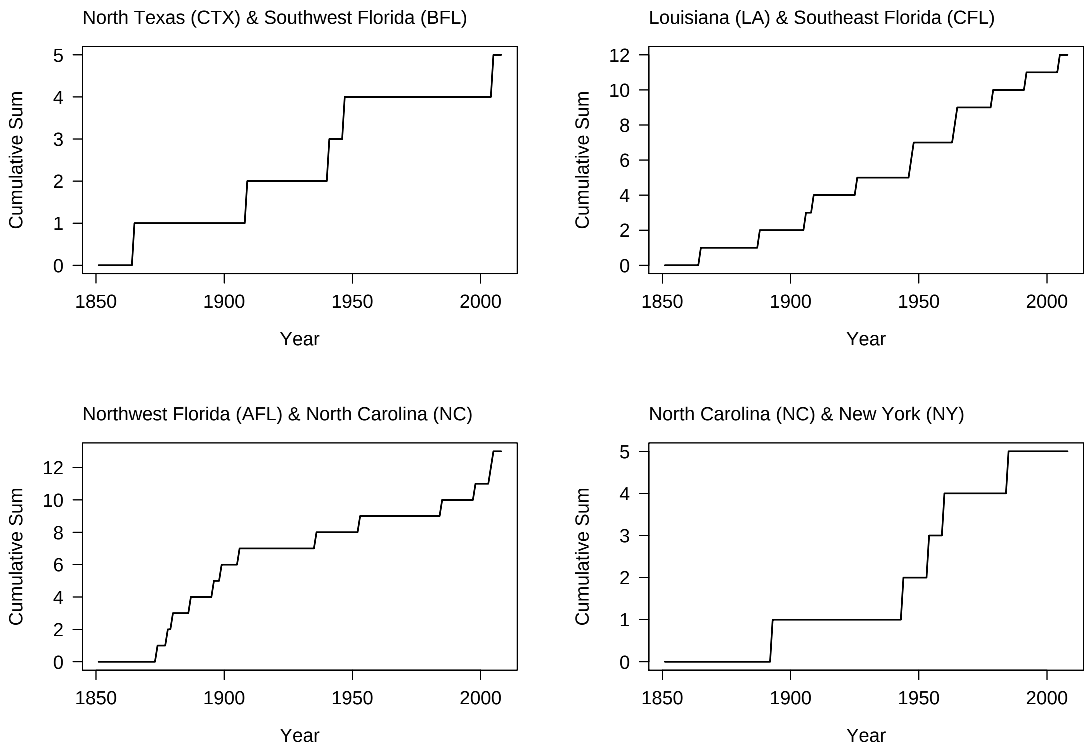

Figure 3.3: Cumulative sum of years in which multiple regions where affected by a hurricane.

an event is created if two regions get hit by a hurricane in the same year and events are cumulatively summed over the years. Unlike the cumulative sum in the previous figure here each step has the same height. Note however that the panels have different scales for the cumulative sum.

Again we see variations in the rates and the changes in rates depending on regions. The overall rate of multiple hit years for Louisiana and southeast Florida is relatively steady, whereas for northwest Florida and North Carolina the period from about 1875 through 1910 was quite active followed by a period of relative inactivity, which appears to have ended around the year 2000.

This chapter introduced the principal data set used in this dissertation and provided some exploratory analyses. Next the relationships between regions affected by the same hurricane using the methods of network analysis are considered.

CHAPTER 4

A NETWORK TO CONNECT HURRICANES ACROSS SPACE

The previous chapter described the hurricane data used in the dissertation and provided an exploratory look at these data. Variations in the landfall rates are shown to be dependent on the region. This chapter will explain how to create a network of hurricanes from a list of their occurrences. The method is applied to the actual set of hurricanes affecting the United States since 1851 and the network is displayed using a few different plots.

The network considered is a network that connects landfalls across space (landfall network). This network of hurricane landfalls is created by considering individual hurricanes that have affected more than one coastal region. For this study the regions are individual states, but Texas and Florida are further subdivided as explained in Chapter 3. The goal is to use methods from network analysis to examine geographic relationships (linkages) between coastal hurricanes affecting the United States.

As mentioned, 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. This research uses network analysis to perform a systematic study of regional hurricane relations. As described in Chapter 2, a network is graph connecting nodes. Nodes in this case represent regions that experienced a landfalling hurricane. If the hurricane affects more than one region then a link is drawn between nodes. The graph is undirected as the link between regions do not differentiate the time order of the regions affected. The procedures for constructing the network are described next using an example.

4.1 Example

The network is constructed in three steps. In step 1, an incidence matrix is obtained from the data set of hurricane occurrences. An incidence matrix lists each hurricane in the data set by row with the columns corresponding to the regions. If the first hurricane in the record affected region one then a 1 is but in the matrix (1, 1) entry. If region two was not affected by the first hurricane, then a 0 is put in the matrix (1, 2) entry, and so on. Thus the incidence matrix shows the occurrence of hurricanes by region. In step 2 an adjacency matrix is computed from the incidence matrix using matrix algebra whereby the incidence matrix is pre-multiplied by its transpose. The transpose of a matrix X, denoted X^T, has the same elements as X only the rows and columns are interchanged. In step 3, the network graph is drawn by connecting regions that have a non-zero entry in the adjacency matrix.

To see how this works, consider the following hypothetical table of hurricane occurrences (Table 4.1). Hurricane one (H1) affected regions 1 (R1) and 3 (R3), but no others. Hurricane two affected regions 1, 2, and 5, and so on. We therefore have a 4 by 5 (hurricanes by region) incidence matrix called X. The adjacency matrix A is obtained as $X^T X$, which results in a 5 by 5 (region by region) matrix as shown in Table 4.2. The diagonal elements of the adjacency matrix are not considered in the analysis.

Table 4.1: 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
H1	1	0	1	0	0
H2	1	1	0	0	1
H3	0	1	0	1	0
H4	1	0	0	0	0

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. Finally the network is constructed directly from the adjacency matrix where values of 1 indicate a link between the regions. Note that two regions affected by the same hurricane at least once over the period of record results in a linkage. Information about how frequently this occurs is lost from this type of analysis.

Table 4.2: Adjacency matrix constructed from the hypothetical incidence matrix shown in Table 4.1. 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.

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

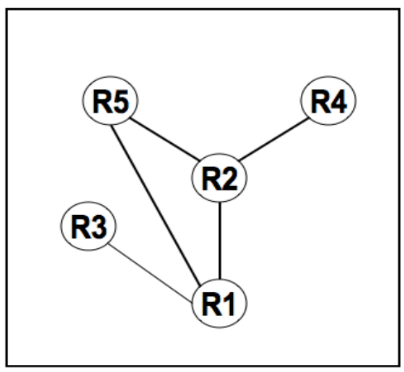

Figure 4.1: Network graph based on the hypothetical set of hurricanes listed in Table 4.1. The network is constructed from the adjacency matrix shown in Table 4.2. Region 2 (R2) is connected to regions 1, 4, and 5.

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Figure 4.1 shows a graph of the network constructed from the hypothetical adjacency matrix. Regions 1 and 2 each have three links, region 5 has two links and regions 3 and 4 each have one link. Since this approach does not distinguish the time order of hits, the links are undirected. Note that the information in the network graph contains the same information as the adjacency matrix.

4.2 Full Network

The above example explains the steps used to construct a hurricane network that connects landfall across regions. It is possible to construct other networks with the same data using different criteria. Figure 4.2 shows the incidence matrix, adjacency matrix, and network graph for the 283 hurricanes affecting the United States during the period 1851 through 2008. To make the matrix fit in the plot, the state regions are shown along the vertical axis and the hurricane occurrences in temporal order are shown along the horizontal axis. A black bar denotes a hurricane affecting a particular region. For instance, central Texas (BTX) was affected by the first hurricane in the record, while both northwest Florida (AFL) and Georgia were affected by the second hurricane in the record. Note that this analysis does not take into account the strength of the hurricane at landfall. The incidence matrix has 283 rows corresponding to all the hurricanes since 1851 and 23 columns corresponding to the states affected.

The adjacency matrix, shown in panel (b) of the same Figure 4.2 is created by pre-multiplying the incidence matrix by its transpose. The black squares show that at least one hurricane over the period of record affected the two corresponding regions. The adjacency matrix has dimension 23 by 23. The matrix is symmetric with the pattern of black squares observed in the lower-left triangle of the matrix matching the pattern in the upper-right triangle. The algebra, plots, and network analysis are done using the R software (R Development Core Team 2006).

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. It is interesting to note if there is any relationship between the frequency of hurricanes in a region and the number of linkages the node has.

As noted above, the network can be mapped in different ways. Figure 4.3 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. Notice that New York and New Jersey have never been affected by the same hurricane during the period of 1851–2008. In particular note the relatively high number of links with northeastern Florida and the regions of New England

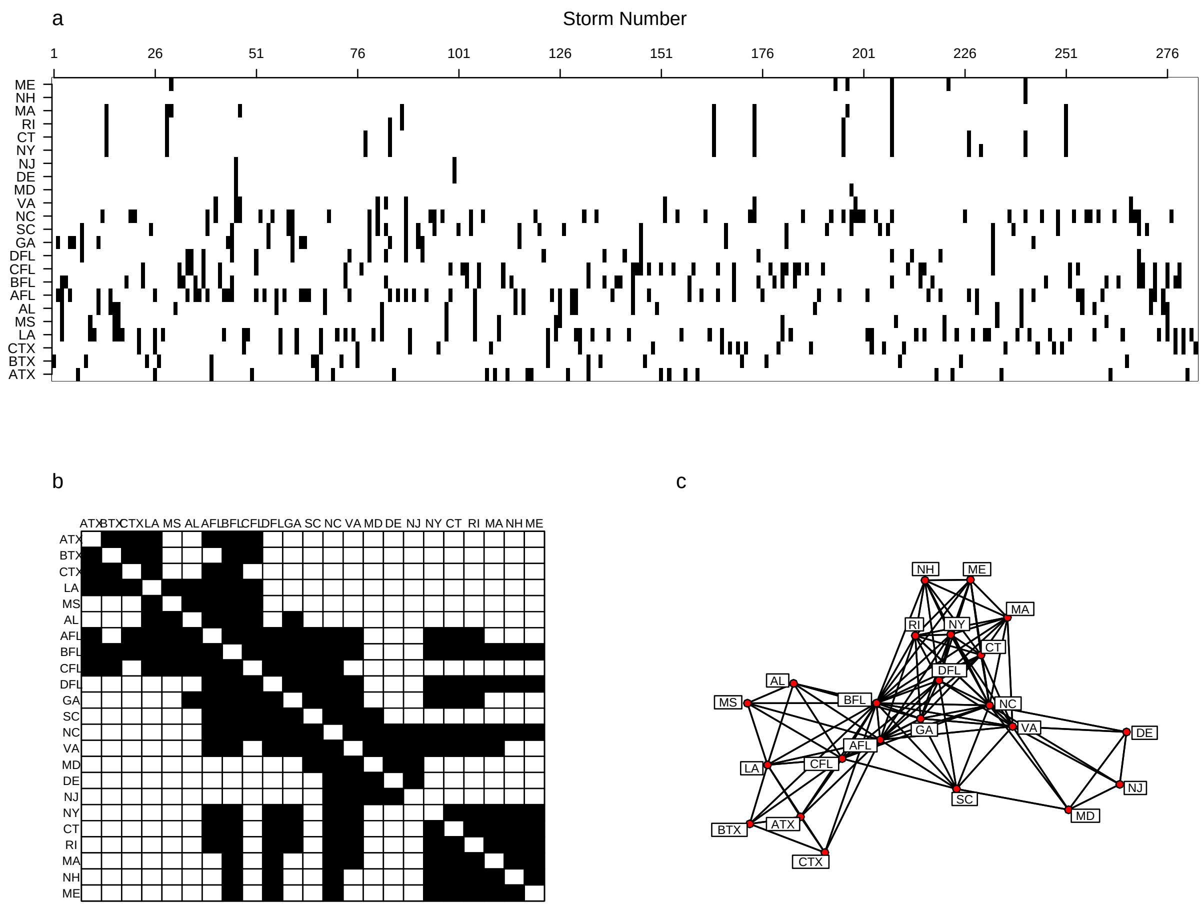

Figure 4.2: The occurrence and network of U.S. regions affected by hurricanes. The incidence matrix (a) shows the regions along the vertical axis and the hurricane numbers along the horizontal axis. The hurricane numbers are the time sequence of hurricanes beginning in 1851. A hurricane occurrence is noted in the incidence matrix as a black dash. Nearby regions experiencing the same hurricane are connected by a long dash. Remote regions affected by the same hurricane are show as discrete dashes. Filling the incidence matrix with 0 for no occurrence and 1 for occurrence then pre-multiplying it by its transpose produces the adjacency matrix (b). The black squares show that at least one hurricane over the period affected the two corresponding regions. The adjacency matrix defines the network, but is displayed as a set of nodes (regions) and links in (c).

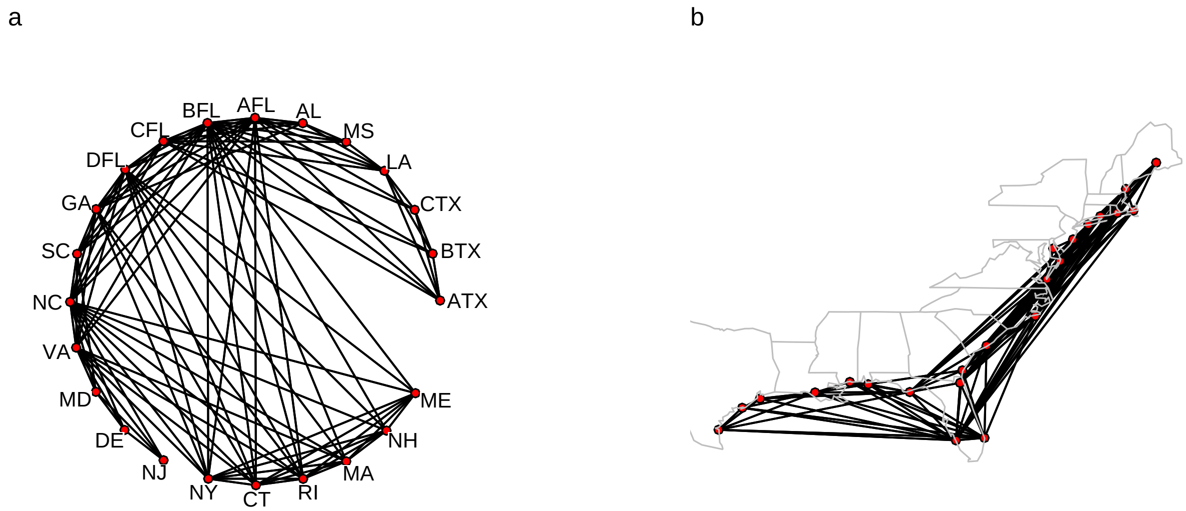

Figure 4.3: The hurricane network mapped on a circle (a) and on the coastal boundary (b). The network is aspatial in that the spatial configuration of the nodes are irrelevant. What is important are the topological characteristics of the network defined and described for the landfall network in chapter 5

as a result of hurricanes recurving out of the Caribbean and moving north northeastward.

This chapter demonstrates how to construct a network of coincident landfall locations using a list of hurricanes by region. The regions correspond to U.S. States affected by hurricanes from Texas to Maine. The construction uses algebra to create an adjacency matrix from the list of hurricanes. The network uses the information in the adjacency matrix directly. A network of all hurricanes affecting the U.S. since 1851 is created. Plots are useful in revealing the topology of the network and can be mapped in various ways. The next chapter examines various topological characteristics of the network using quantitative metrics.

CHAPTER 5

GLOBAL AND LOCAL METRICS OF THE LANDFALL NETWORK

The previous chapter explained how to create a network of hurricanes from a list of their occurrences. The method was applied to the actual set of hurricanes affecting the United States since 1851 and the network was displayed using a few different plots. In this chapter structural properties of the network are examined quantitatively using various topological metrics.

The structural properties can be divided into two types: local and global. Here special R routines developed by Butts (2006) under the *sna* package and by Csardi (2007) under the *igraph* package are used.

Lets begin by considering three measures of node centrality. Centrality as used here is restricted to the idea of node centrality (local), while the term centralization is used to refer to particular properties of the graph structure as a whole (global). Centralization, therefore, refers to the overall cohesion or integration of the graph rather than the relative prominence of the nodes (Scott 1991). A node is locally central if it has a large number of connections with other nodes in its immediate environment if, for example, it has a large neighborhood of direct contacts. On the other hand, a node is globally central, when it has a position of strategic significance in the overall structure of the network. Local centrality is concerned with the relative prominence of a focal node in its neighborhood, while global centrality concerns prominence within the whole network (Scott 1991). More loosely defined centrality is considered 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 of centrality we consider are degree, closeness, and betweenness.

The “degree” (prestige) of a node (vertex) is its most basic structural property, the

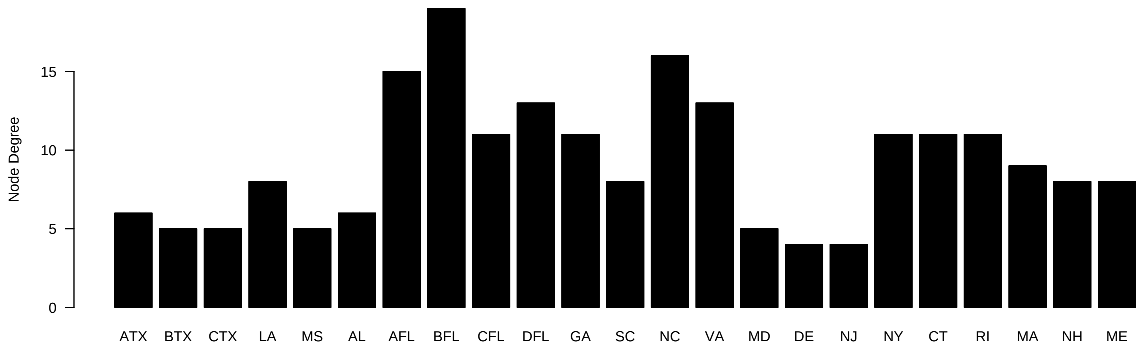

Figure 5.1: The node degree is the number of links connected to the node. Here the degree represents the number of regions affected by hurricanes that have affected the particular region. For instance, south Texas has degree 6 meaning that 6 other regions have been affected by hurricanes affecting south Texas.

number of links (edges) connected to a node. A directed graph has both an in-degree and out-degree for each node, which are the numbers of incoming and outgoing edges respectively. As noted previously, this work considers only undirected networks so no differentiation is made between in–degrees and out–degrees. In the landfall network the degree of the node is the number of regions linked to it. The link is created by virtue of having at least one hurricane in the record affect both regions.

Figure 5.1 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 northwest Florida node has degree 15 being linked to many other regions. Nodes with the largest degree include southwest Florida and North Carolina. Regions in the northeast with high prestige include New York, Connecticut and Rhode Island. Note the relatively low level of prestige for the states along the Gulf coast.

There are a total of 212 degrees in the network (sum of all node degrees). Since there are 23 nodes, twenty percent of the network consists of 5 nodes (approximately). Thus the top 20% of the nodes account for 35% of the total number of degrees. The degree distribution is the number of nodes with k degrees. Table 5.1 list the degree distribution for the hurricane network.

Table 5.1: Degree distribution of the hurricane landfall network. k is the node degree and N is the number of nodes with that degree. The relatively small number of nodes makes it difficult to characterize the network based on the degree distribution, but it does not appear to be a scale-free network where a few nodes have the majority of prestige.

k	N
1–5	6
6–10	7
11–15	8
16–20	2

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. Remembering that 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

$$C_c(v) = \frac{|V(G)| - 1}{\sum_{i:i \neq v} d(v,i)} \tag{5.1}$$

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 5.2 shows the closeness index by region. Here again we find southwest Florida and North Carolina with the highest values. The path hurricanes sometimes take from Florida to North Carolina makes these regions important in the landfall network. Less important to the network are the middle Atlantic regions of Maryland, Delaware, and New Jersey. Figure 5.4 depicts the closeness values of the nodes in the landfall network using a color coding.

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

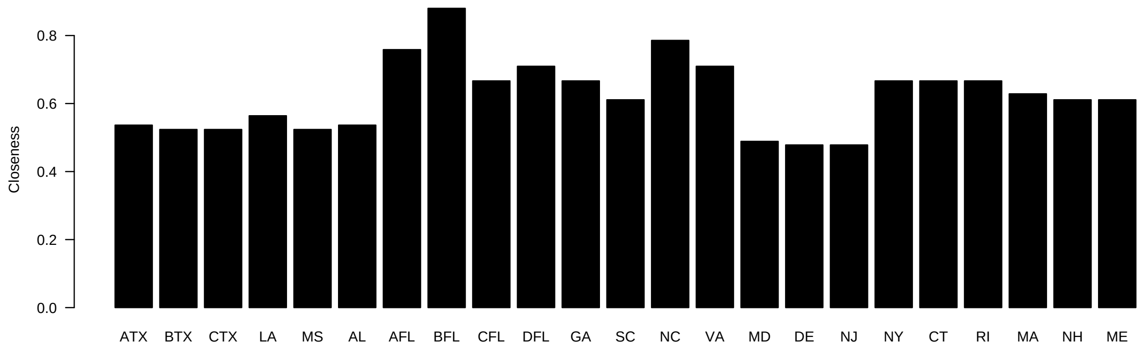

Figure 5.2: The node closeness is an index that quantifies the number of paths through the node that are geodesics.

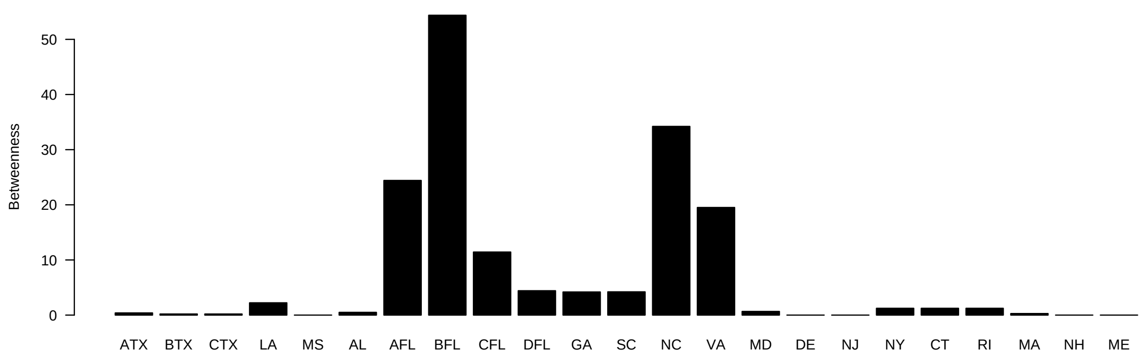

Figure 5.3: Node betweenness. Betweenness of node V measure the number of "times" a any other node needs to go through the V by the shortest path.

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 5.3 shows the betweenness values for each of the nodes in the hurricane network. The plot is similar to the plots of node degree and node closeness in that southwest Florida and North Carolina come out on top, but is different in that the difference between these two regions and much of the rest of coast is magnified. That is, southwest Florida and North Carolina have much higher values of betweenness than do most of the other regions. Thus b

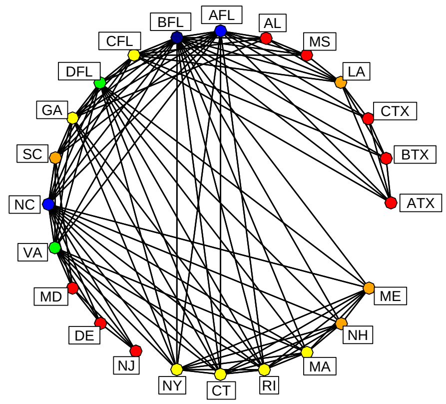

Figure 5.4: The color (from red=min to blue=max) represent closeness values for the hurricane landfall network. The "closeness" of a node provides an index for the extent to which a given node has short paths to all other nodes in the graph. North Carolina, northwest Florida and southwest Florida have the highest values of closeness in the landfall network.

a

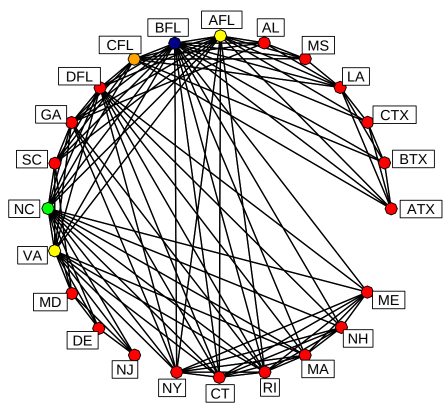

Figure 5.5: The color (from red=min to blue=max) represent betweenness values for the hurricane landfall network. Notice that southwest Florida (BFL) has very high value of betweenness. This indicates that southwest Florida is affected by storms that have also affected at least one other location.

Table 5.2: Correlation between average regional hurricane rates and three local measures of network centrality.

	Degree	Closeness	Betweenness
r	0.498±0.18	0.469±0.19	0.558±0.18

it appears as if betweenness is a topological metric that better differentiates the regions. Interestingly, though it receives very few hurricanes Virginia is a state that shows the fourth highest betweenness value. Figure 5.5 shows the node betweenness for the landfall network using color coding.

The correlation between rates by region calculated in Chapter 3 and the degree, closeness and betweenness of the landfall network are listed in Table 5.2. Betweenness is most strongly correlated to average landfall rates by region. The importance of a node (region) to the spatial linkages between regions is captured by the concept of betweenness. Betweenness indicates which regions are linked geographically to other locations. Regions (nodes) with high values of betweenness are those places that are affected by the same hurricane that came from or went to another region.

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 the example from Chapter 2 where the citation network of hurricane researchers was considered, two authors are connected in the network if they site each other's work. Consider an author connected with two others, if these linked 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. The question of how many years in the network are required for the network to be fully connected is an important question. A network is considered connected if there is a path between every pair of nodes in the network. Table 5.3 shows information that should be considered if connectedness is an attribute required for proper analysis of the network. In the case of this study connectedness is achieved by the first thirty consecutive years.

Table 5.3: Shown below are blocks of time progressing in a cumulative fashion. Where, N is equal to the number of years in the block. The starting year is 1851, so for instance, $N = 20$ is the first twenty years in the record 1851–1870. Then $N = 30$ is 1851–1880, $N = 75$ is 1851–1925 and so on until $N = 158$ which is all the years 1851–2008. Notice that complete connectedness is not achieved until all 158 years are used. This is due to that fact that New Hampshire was not affected by a hurricane that also affected another region until 1960 with hurricane Donna. It seems that the network is well connected when using at least the first 30 consecutive years of the record. This does not mean any 30 year increment is sufficient. Breaking the network down in to non-overlapping blocks of 30 will help tease out regions not affected (affected) by multiple landfall events but the connectedness values fluctuate significantly (not shown).

N	20	25	30	50	75	100	158
Connectedness	0.25	0.30	0.91	0.91	0.91	0.91	1.00

This chapter presented results from examining the landfall network using local and global metrics. Productive information came from the examination of the network metrics. Degree, closeness and betweenness each provide unique pieces of information about the landfall network structure. It was also shown that had the network been required to be fully connected it would have to incorporate at least 109 years that is 1851–1960 in to the data. It was also found that as long as one uses at least the first 30 consecutive years of the landfall record that 0.91 connectedness is achieved. The next chapter investigates the landfall network conditioned on three large–scale climate factors.

CHAPTER 6

LANDFALL NETWORKS CONDITIONED ON CLIMATE

The last chapter provided useful information related to the landfall network. Resulting centrality metrics indicated that nodes with the largest degree included southwest Florida and North Carolina. Relatively low node degree exists for the states along the Gulf coast. Resulting values of closeness show that the path hurricanes sometimes take from Florida to North Carolina makes these regions important in the landfall network. Less important to the network are the middle Atlantic regions of Maryland, Delaware, and New Jersey. Betweenness is a topological metric that better differentiates the regions. Betweenness values show southwest Florida and North Carolina have much higher values of betweenness than do most of the other regions. These metrics are important tools to be able to compare and contrast network structure. This chapter will use the same steps outlined in Chapter 4 to construct landfall networks based on large scale climate variables.

Thus far the research has assumed that all years are the same and that hurricanes affecting the coast are independent of one another. While the second assumption is reasonable, the first assumption assumes that hurricanes are unaffected by climate variations. This assumption is not completely warranted as a number of studies have shown hurricanes are more likely during La Niña conditions and when the ocean temperatures are warm (Gray 1993; Goldenberg et al. 2001; Elsner and Kara 1999). Moreover Elsner (2003) has shown that to better understand and predict regional hurricane probabilities it is important to consider climate factors that influence where they track. In this regard it is interesting to consider how the hurricane landfall network properties change with climate factors.

Here three variables that have previously been related to U.S. hurricane activity are considered. The variables include an index of the North Atlantic Oscillation (NAO), an index of the El Niño-Southern Oscillation (ENSO), and North Atlantic ocean temperatures (SST).

Ordered factors are created by considering 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 (above and below normal NAO, above and below normal SST, above and below normal SOI).

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 Niño 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 the 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, August through October average of the SST anomalies are used as the 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). The pairwise correlation between each of the climate variables is small, so it is reasonable to treat them as largely independent.

Table 6.1 summarizes the network properties conditional on each of the factors. Notice 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 Niño event in the

Table 6.1: Network properties conditional on three separate climate factors. The three separate climate factors include the North Atlantic oscillation (NAO) the southern oscillation (SOI) and Atlantic SST. The mean values are given along with the plus and minus one standard error.

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

tropical Pacific, the mean nodal connectivity is 4.8$\pm$0.79. This value is significantly less than the value of 7.2$\pm$0.98 for the La Niña network of U.S. hurricanes. Furthermore, there is 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.

The statistically significant lower values of mean degree of the landfall network during El Niño years compared to La Niña years is due to fewer hurricanes affecting the coast during El Niño. El Niño conditions tend to result in greater wind shear across the North Atlantic inhibiting the development of hurricanes. Interestingly though the betweenness values is higher during these El Niño years indicating the hurricanes that do affect the coast tend to affect more than one region. This chapter examined local metrics of landfall networks that were created dependent on three large scale climate factors. It is discovered that the hurricane network changes substantially between above and below phases of the ENSO. There is more connectivity during warm SST years compared to cool SST years. The next chapter will examine a time series of U.S. hurricanes from the perspective of network theory.

CHAPTER 7

A NETWORK TO CONNECT HURRICANES ACROSS TIME

Part one of this dissertation examined the spatial distribution of U.S. hurricane activity using ideas and concepts borrowed from network theory. The network was constructed by considering regions affected by hurricanes as nodes and a link between the nodes defined by the occurrence of a single hurricane affecting more than one region. A network constructed in this way is useful in identifying the regions over which multiple loss events from a hurricane may occur. Interestingly, regions experiencing the greatest risk of hurricanes are not necessarily the regions that are well connected in the network. For instance, as was demonstrated, the state of Louisiana is affected relatively frequently by hurricanes but these same hurricanes tend not to affect other regions of the U.S. coast. That is, cyclones that affect Louisiana tend to *only* affect Louisiana. Of course, there are exceptions.

Visibility Network

Part two of the dissertation examines the year-to-year variation in U.S. hurricane activity from the perspective of networks. This requires a mapping of the time series of hurricane counts into a network. This is an idea that is new to network analysis. The research in this part is based on the very recent work by Lacasa et al. (2008), who demonstrate how to consider time-series data as a network by using a visibility algorithm. The resulting network inherits several properties of the series in its structure. For instance, periodic time series convert into regular graphs and random time series convert to random graphs.

For illustration, in Figure 7.1(a) the time series of U.S.hurricane counts from 1851 through 1870 are shown as bars. Think of these bars as a discrete landscape. Then a bar is connected to another bar if they are “visible” to one another. The connections are shown as thin lines linking the bars. Of course the operation is commutative (if bar A can see bar B, then bar B can see bar A). The links represent a “line of sight” for each bar. No links cut through any bars. In this way each value in the time series is linked in a network.

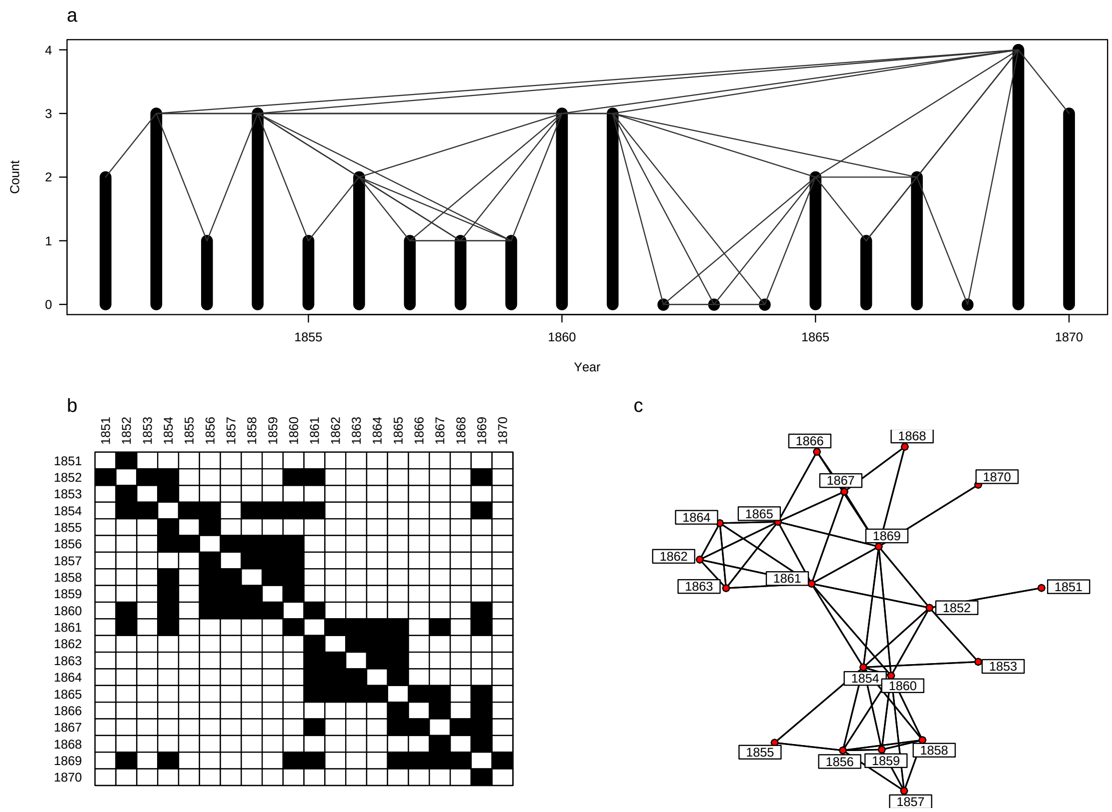

Figure 7.1: a) Time series of U.S. hurricane counts from 1851–1870 with links defined by the visibility algorithm. b) Adjacency matrix of constructed from the visibility links. c) Visibility network constructed from the adjacency matrix. The algorithm is based on the work of Lacasa (2008).

Following Lacasa et al. (2008), let h_a be the U.S. hurricane count for year t_a and h_b the count for year t_b, then these two years will be linked if for any other year t_i with count h_i

$$h_i < h_b + (h_a - h_b)\frac{t_b - t_i}{t_b - t_a} \tag{7.1}$$

In this way each year sees at least its nearest neighbors (before and after) and the network is invariant under rescaling of the horizontal and vertical axes as well as under horizontal and vertical translations (Lacasa et al. 2008). Lacasa et al. (2008) describes the visibility graph as a tool that can be used in time series analysis. An algorithm for converting the time series of hurricane counts to a visibility graph was written in R by Thomas Jagger for this research and is provided as Appendix B. To better explain the creation of the visibility network an example is given in the next section.

7.1 Example

Continuing with the first 20 years of the hurricane record (1851–1870) as an example, recall from part one of the dissertation, that a line (edge or connection) is defined by its two endpoints, which are the two nodes that are incident with the line. In part one, two nodes (or locations) are incident with each other if the same hurricane affected both locations (nodes). Now with the time series data, two years (nodes) are considered incident, when they are "visible" to each other in time. Thus a connection is a linkage between two nodes in the visibility network.

First the time series of U.S. hurricane counts is connected with links defined by the visibility algorithm. This allows us to view the time series with a series of connecting lines to those years that are "visible" to other years. Figure 7.1(a) displays the time series and resulting visibility lines. The visibility algorithm creates an adjacency matrix that specifies which years are connected (visible) to which of the other years. The adjacency matrix is shown in Figure 7.1(b). The matrix entrees shown in black indicate a linkage (visibility) between years. Thus it is clear from the adjacency matrix that 1852 can "see" 1851, 1853, 1854, 1860, 1861, and 1869, while 1851 can only "see" 1852. The adjacency matrix thus defines a set of linkages between years. A year is not connected with itself so blanks are noted along the matrix diagonal. Large values will, in general, result in more linkages, but especially if they are rare among years with lower counts.

The network graph shown in Figure 7.1(c) arises, as before, by plotting the linkages described in the adjacency matrix. The years are shown as nodes and labeled and the links represent the connections between years based on the visibility algorithm. Here it is obvious that 1869 is well connected while 1853 is not. Again, years with many hurricanes next to years with no or few hurricanes will be better connected than years with few hurricanes or years next to years with many hurricanes. This can be seen by comparing 1858 with 1866. Both years had one U.S. hurricane, but 1858 is next two years that also have only one hurricane so it is connected with four other years. In contrast, 1866 is next to two years each with two hurricanes so it has the minimum of two linkages.

It is my contention that a network constructed from the time series of U.S. hurricane counts may be of importance for understanding hurricane climatology that may not be accessible from more routine approaches. For instance, since the network preserves the properties of the time series, it is of interest to see if the network can detect departures from a random Poisson process (Elsner and Schmertmann 1993). Such a departure might take the form of significant temporal autocorrelation so that years of low hurricane activity tend to follow years of low activity and years of high activity tend to follow years of high activity. From the definition of visibility, years of high activity that tend to follow years of high activity will not be as connected in the network as years of high activity followed by years of low activity.

Once the network is constructed in this way, it is possible to examine its various topological characteristics using different metrics. These metrics can be of a local nature (a value at each node) or of a global nature (a single value for the entire network). The next section will cover the creation of the visibility network of hurricanes affecting the U.S. from 1851–to present. Also covered is the examination of various metrics of network connectivity.

7.2 Full Network

In this section a visibility network of hurricanes affecting the U.S. will be created. The steps outlined in the last section are the same steps that are used to create the visibility network for all the years. Once the visibility network is created the local and global metrics can be examined and those result will also be covered in this chapter. The example from the last section explains the steps to construct a visibility network that connects landfall across time. Using these steps the full visibility network is created.

The full set of U.S. hurricane counts from 1851–2008 are shown as a time series in Figure 7.2. The plot reveals some interesting characteristics. First, the annual counts range from zero to a maximum of 7. There was only one year with 7 U.S. hurricanes and that occurred in 1886. Second, the mean number of U.S. hurricanes is 1.7 with a standard deviation of 1.4. Assuming an independent Poisson process, this indicates that there is an 82% chance of a U.S. hurricane in any given year and a 9% chance of more than three U.S. hurricanes in any given year. Third, there does not appear to be an overall upward or

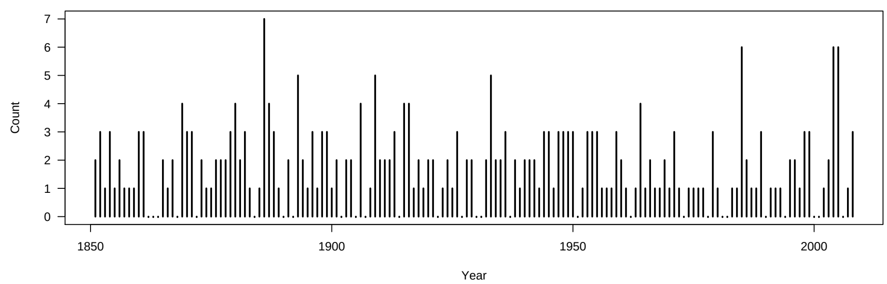

Figure 7.2: Frequency of hurricanes affecting the United States over the period 1851–2008. The mean annual rate is 1.7 hurricanes per year.

downward trend in the counts.

Keep in mind that a graph is a set of nodes and a set of edges between pairs of nodes. The graph is a visual representation of the structure of the network. The network consists of a graph and additional information on the nodes or the linkages of the graph. That is; a network equals its graph plus data. The node is smallest unit in a network. In part one, the nodes are the geographic locations of U.S. hurricanes and the connections are whether the regions were both affected by the same hurricane. Here in part two, the nodes are years and the connections are whether the year's count can seen by another year's count. Thus the visibility network based on time series data is more of an abstract construction than is the location network and it is not clear *a priori* whether there is anything useful to be gained with this perspective.

The visibility network shows the linkages between years that are "visible" to other years in time. The network graph shown in Figure 7.3 arises, as before, by plotting the linkages described in the adjacency matrix. The years are shown as nodes and labeled and the links represent the connections between years based on the visibility algorithm. In the hurricane visibility network the degree of the node is the number of years that year can "see" other years within the network of hurricanes affecting the U.S. over time. Nodes with high degree are more likely to be found in dense sections of the network. Average degree can be compared between networks of different sizes (Nooy et al. 2005). Average degree (or average local centrality) for the visibility network (1851–2008) is 6.8. Therefore the average year (node) can see about 7 other years (nodes) in the visibility network. Figure 7.4(b) shows many years

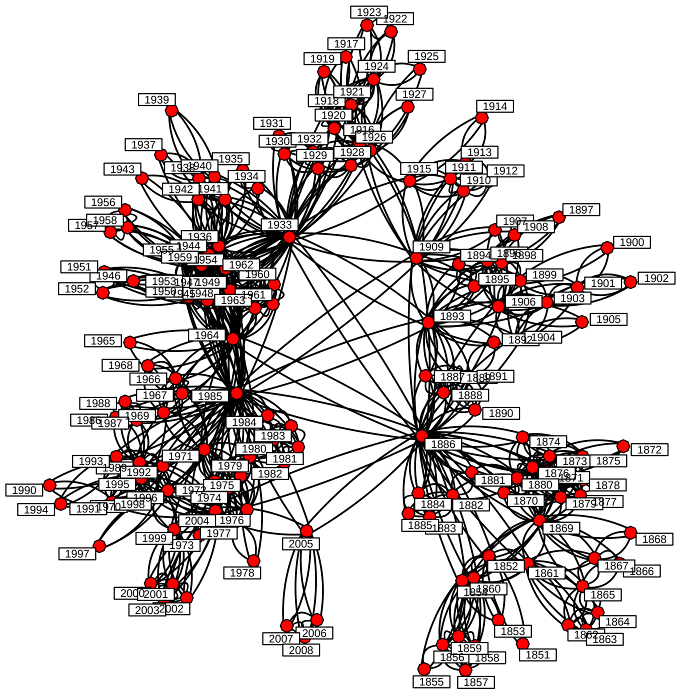

Figure 7.3: Visibility network of hurricane affecting the United States 1851–2008. The network is constructed by considering the visibility of counts from year to year.

with few lines of visibility, hence limited connectivity to other years. There are few years with many lines of visibility, therefore, many linkages to other years. Those years with high hurricane count have more visibility in the network than those years that have less storms.

Closeness shown in Figure 7.4(c) is an index that quantifies the number of connections through years that are geodesics. Remember that geodesic is the shortest path between to nodes, or in this case the shortest paths between two nodes visible to each other in time. Closeness measures how many steps are required to access every other node from a given node. Figure 7.5 represents closeness values for the visibility network. The closer a node is to all other nodes, the the more visible it is, and the higher the global centrality. Closeness in the visibility network is the degree a year is directly visible to all other years in the

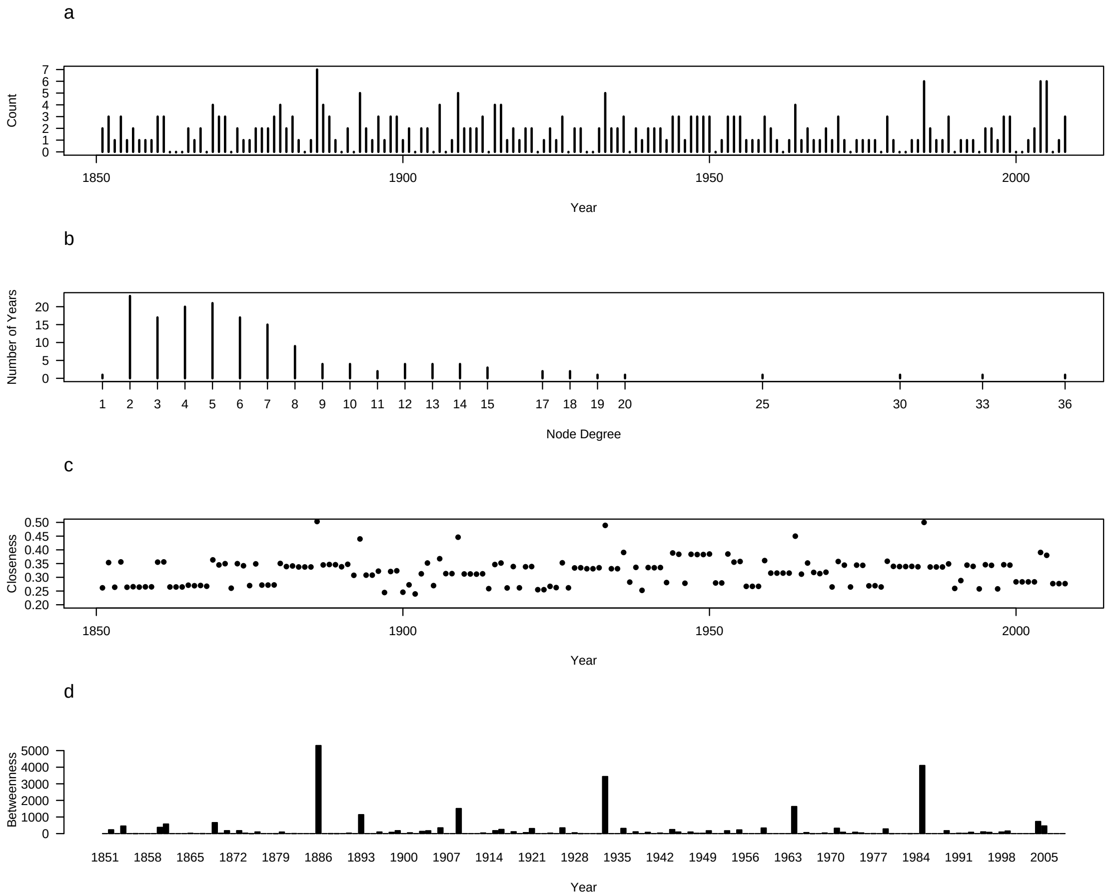

Figure 7.4: Metrics of the visibility network. The visibility network is constructed from the annual counts of hurricanes affecting the United States over the period 1851–2008.

network. It reflects the ability for one year to see through the network of years. Years with high frequencies of hurricane counts will be able to see more years in the network. For instance 1886 with a count of 7 and a closeness value of 0.50, can see 30 other years in the network. The importance of a node to the visualization between years is captured by the concept of betweenness centrality (Figure 7.4(d)). In this perspective, a year is more central if it is linked in more visibility chains between other years in the network. High betweenness centrality indicates that a year is an important intermediary in the visibility network. Visibility chains are represented by geodesics and the betweenness centrality of a node is simply the proportion of geodesics between pairs of other nodes that include the node. Figure 7.6 shows the betweenness values of the visibility network. The nodes are

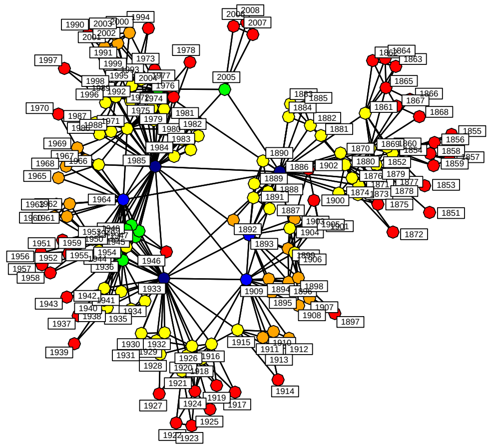

Figure 7.5: The color (from red=min to blue=max) represent closeness values for the visibility landfall network. The "closeness" of a node provides an index for the extent to which a given node has short paths to all other nodes in the graph. 1886, 1909, 1933, 1964 and 1985 have the highest values of closeness in the visibility network.

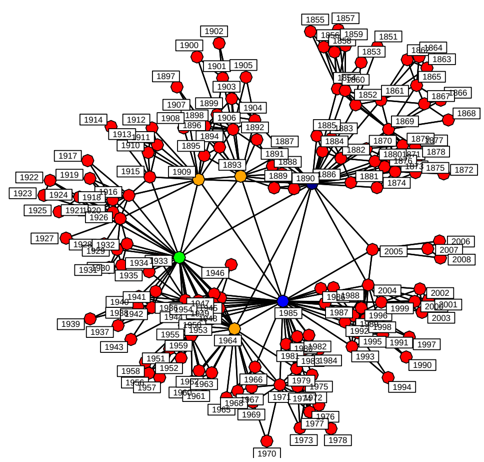

Figure 7.6: The color (from red=min to blue=max) represent betweenness values for the visibility network. Notice that 1985 has very high value of betweenness. This indicates that this year is visible by many other years in the network.

distinguished by a range of colors (from red=min to blue=max) that represent betweenness values for the visibility network. The year 1985 has very high value of betweenness. This indicates that this year is visible by many other years in the network. Global metrics are also of interest for the visibility network. The diameter of the network is the maximum geodesic distance over the network. Here we find that this distance is 5. Thus the maximum shortest path between any two years is 5 links. This is identical to the landfall network of part one. As described in Chapter 5, 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 visibility network is 0.48 indicating that slightly less than half of all years that are linked to a specific year are also visible to each other. Hence few years with many links and many years with few links.

There are a total of 1094 degrees in the network (sum of all node degrees). Since there are 158 nodes, twenty percent of the network consists of 31 nodes (approximately). Thus the top 20% of the nodes account for 25% of the total number of degrees. The degree distribution is the number of nodes with k degrees. Table 7.1 list the degree distribution for the hurricane network.

Table 7.1: Degree distribution of the visibility network. k is the node degree and N is the number of nodes with that degree. The relatively small number of nodes makes it difficult to characterize the network based on the degree distribution, but it does not appear to be a scale-free network where a few nodes have the majority of prestige.

k	N
1–5	82
6–10	49
11–15	17
16–20	6
21–25	1
26–30	1
31–35	1
36–40	1

Table 7.2: Correlation between annual frequency of hurricane landfalls (1851–2008) and three local measures of network centrality. Degree has the highest correlation to annual frequency of hurricane landfalls.

	Degree	Closeness	Betweenness
r	0.753±0.05	0.736±0.05	0.598±0.06

The correlation between the network local metrics and the frequency of U.S. affecting hurricanes is shown in Table 7.2. The largest correlation is between frequency of landfalls and node degree. Years with high degree are more likely to be found in dense sections of the network. This means that there are particular years (nodes) that have many connections or are visible by many other years in the network.

Using the visibility algorithm a network was created using the annual U.S. hurricane landfall counts (1851–2008). First an example is outlined and then the full network is created. Subsequent analysis of the network metrics reveal interesting information about the ability of one year to "see" other years through time. Next an investigation into whether there are differences in the visibility network based on where the hurricane occurrence took place.

7.3 Gulf, Florida, and East Coast

It is possible to construct other visibility networks with the same data using a different criteria. It is interesting to see if there is a difference in the network structure dependent on whether the hurricane occurrence took place on the Gulf, Florida or East Coast. Where the Gulf Coast is comprised of south, central and north Texas, Louisiana, Mississippi and Alabama. All of Florida as a separate region is included and the East Coast is all the coastal states from Georgia north to Maine. Applying the concepts from section 7.2, each region is compared against the other for the same time frame (1851–2008). Three separate visibility networks are created using the visibility algorithm. Figures 7.7, 7.8 and 7.9 represent visibility networks for the Gulf, Florida and East Coast respectively. Notice that depending on which region you are looking at, the years that are central to the networks change. For instance the Gulf Coast years 1852, 1871, 1886 and 1964, are those with higher nodal connectivity. Where as for the East Coast network 1861, 1893, 1955 and 2004 have more local centrality in the visibility network. This indicates that even though the networks represent the same time frame, different years are more visible to other years dependent on the location. This is because there is a tendency for years that are active along the Gulf Coast to be inactive along the East Coast and vice versa. This geographic seesaw in activity along the U.S. coast has been speculated to result in part by the North Atlantic oscillation (Elsner et al. 2000).

Global properties of the network are also of interest. Shown in Figure 7.10 are the resulting local and global metrics for each area. The average degree for each region are quite similar. Florida has a slightly lower average degree indicating that there is less time between years visible to other years. This shows that Florida tends to have a more constant rate of landfalls. The closeness for the various regions remains fairly equal, indicating that the number of steps required to access every other year from a given given stays the same. It makes sense that closeness is similar because at minimum each year can see the year before and after, it would be difficult to determine from closeness how long before each region had a high frequency of counts. Betweenness really has the highest variability between the regions. Notice that the East Coast has a much higher maximum betweenness. This means that there are more years of single count occurrences between years with higher than one landfall counts.

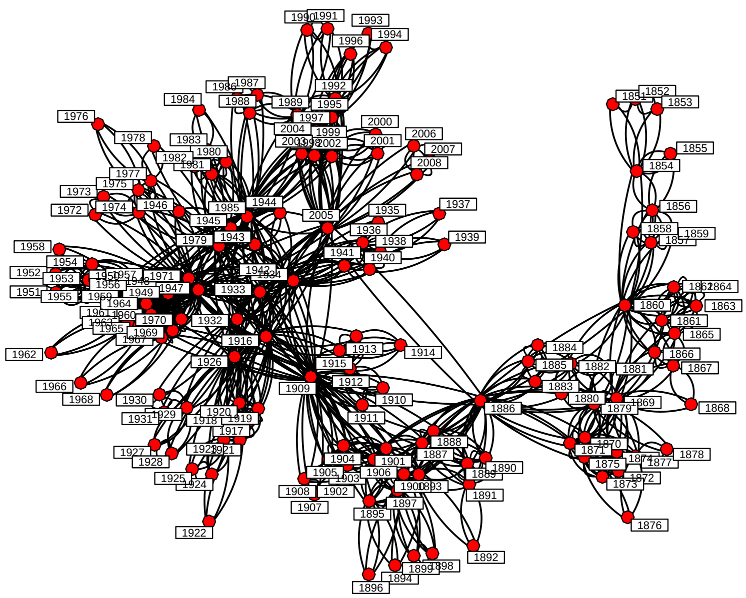

Figure 7.7: Visibility network of hurricanes affecting the Gulf Coast over the period 1851–2008. Years with many links include 1852, 1871, 1886, and 1964.

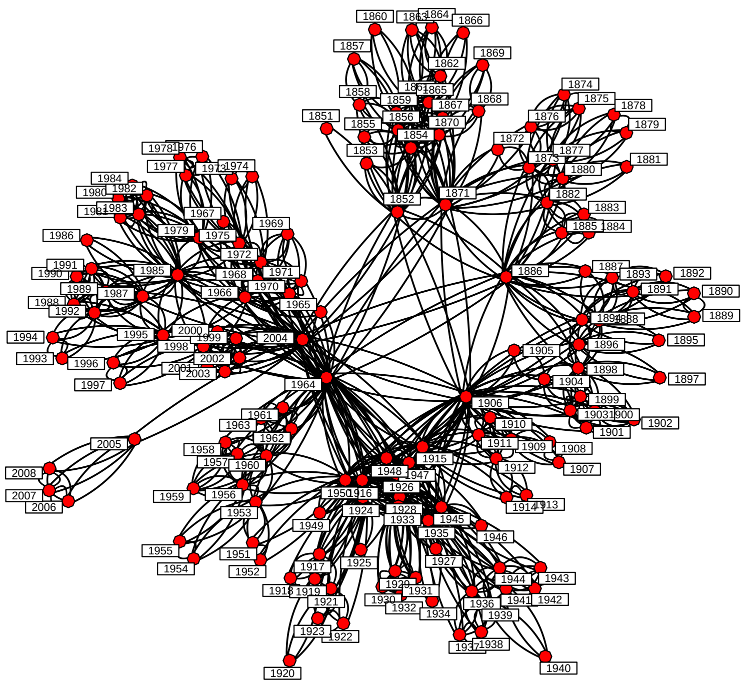

Figure 7.8: Visibility network of hurricanes affecting Florida over the period 1851–2008. The years 1964 and 2004 are well-connected in the Florida hurricane network.

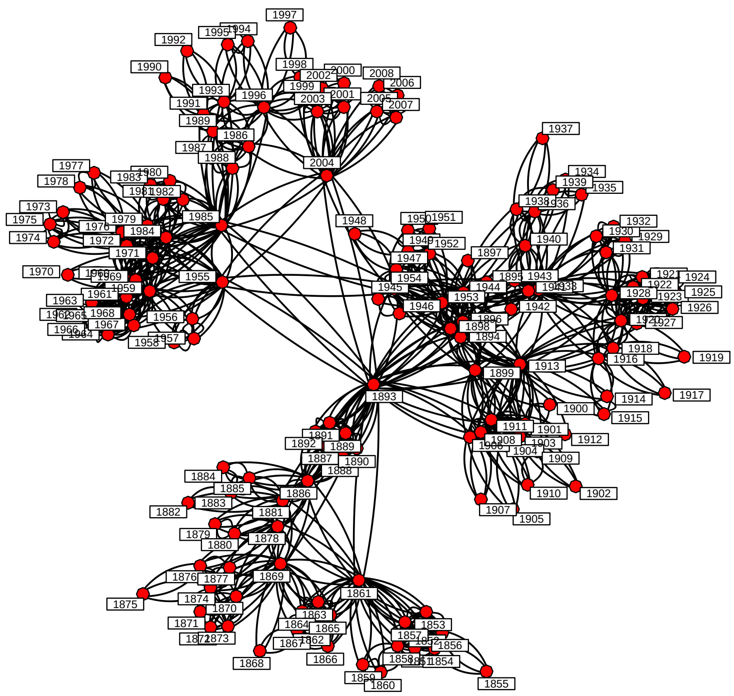

Figure 7.9: Visibility network of hurricanes affecting the East Coast over the period 1851–2008. Years of high visibility include 1861, 1893, 1955 and 2004.

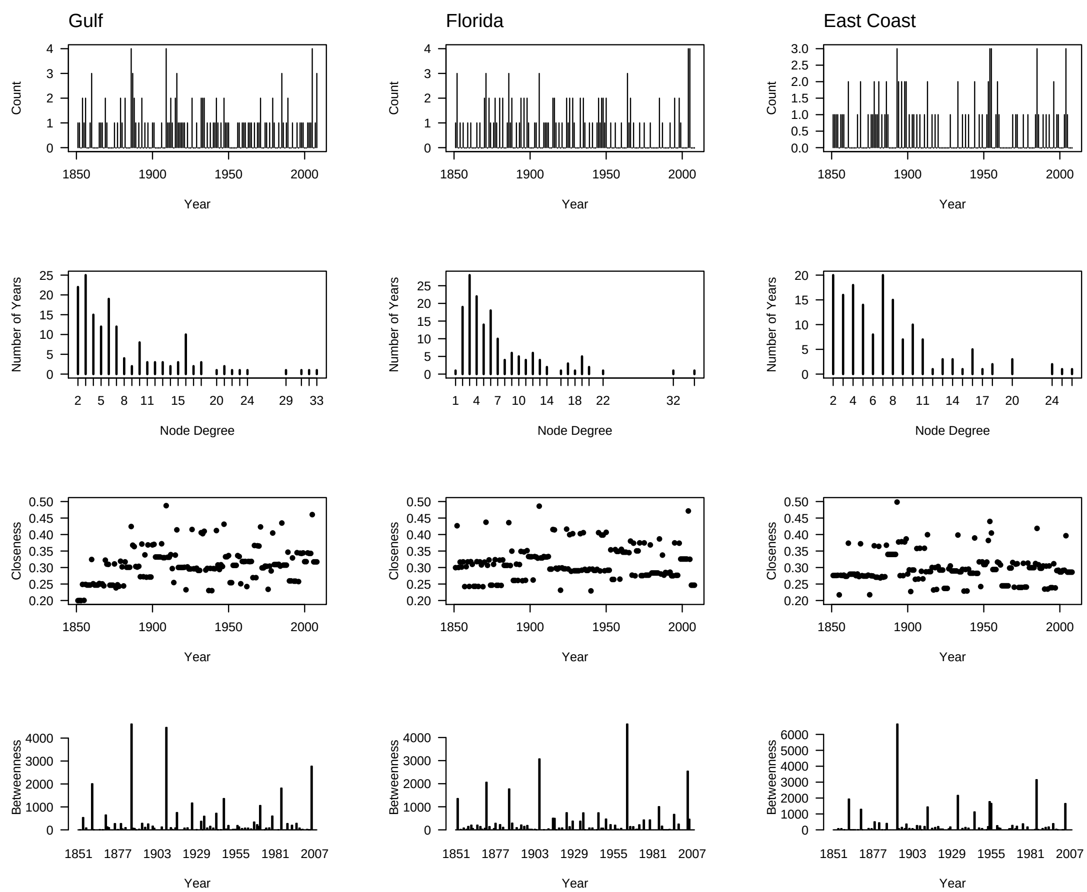

Figure 7.10: Metrics of the visibility networks constructed from hurricane occurrences over the Gulf, Florida and East Coast. The panels are organized vertically with Gulf coast activity shown in the left column, Florida activity in them middle column and East coast activity in the right column. Each row provides a different plot. the top row shows th time series of counts, the second row shows the degree distribution, the third two shows the node closeness as a function of year and the bottom row shows the node betweenness as a function of year

The global properties of the network are shown in Table 7.3. The diameter of the network is the maximum shortest distance over the network. Here we find that 7, 6, and 6 are the diameters for Gulf, Florida and East Coast, respectively. The clustering coefficient is the probability that adjacent years of a year are connected. The clustering coefficients for the Gulf, Florida and East Coast visibility networks are 0.57, 0.48 and 0.55, respectively. So for the Gulf and East Coast networks slightly more than half of all years that are linked to a specific year are also visible to each other. Florida shows less than half, indicating that less than half of all years that are linked to a specific year are also visible to each other.

Table 7.3: Topological characteristics of the visibility network for the Gulf coast, Florida, East coast and all coast (U.S.). Comparison

	Gulf	Florida	East Coast	U.S.
Max Deg.	33	35	26	36
Mean Deg.	7.9±0.52	6.9±0.45	7.5±0.41	6.9±0.45
Max Clos.	0.48	0.52	0.50	0.50
Mean Clos.	0.30±0.004	0.31±0.004	0.30±0.004	0.32±0.004
Max Betw.	4613	4585	6653	5304
Mean Betw.	184±49	177±44	193±54	173±50
Clustering Coeff.	0.57	0.49	0.55	0.48
Diameter	7	6	6	5

It is interesting to note that the average topological characteristics of the Florida visibility network is similar to the overall U.S. visibility network. This means the characteristics of the interannual variability of Florida hurricane activity matches that of the U.S. as a whole.

7.4 Relationship of the Visibility Network to Climate

The last section covered visibility networks dependent on whether the hurricane occurrence took place on the Gulf, Florida or East Coast. This section covers the relationship of the visibility network to large scale climate variables. Using the same methods used in Chapter 6 six networks are constructed. Here three variables are considered 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 Niño-Southern Oscillation (ENSO), and North Atlantic ocean temperatures (SST). Ordered factors are created from these variables by considering whether a year is above or below the long term average based on seasonal averages. Six separate networks are constructed using only hurricanes from years that fall into the six factor groups.

Table 7.4 summaries the local and global metrics of the visibility network. Here it can be seen that the visibility network changes the most between above and below phase of the ENSO. Comparison of the mean degree for networks of different lengths problematic as networks from longer time series will have more chances for links. Betweenness is a better measure of differences between the visibility networks conditioned on climate. Notice that maximum betweenness is lower with below average values of the SOI and SST. This indicates that those visibility networks have few years with visibility to many other years, hence a more year-to-year consistency in landfall rates.

The results show that of the three climate variables considered here, ENSO appears to have the greatest influence on the topology of the visibility network. When the SOI is above normal, ocean temperatures in the equatorial eastern Pacific Ocean are below normal indicating a La Niña event. As mentioned previously, La Niña events are associated with a higher probability of hurricanes affecting the United States (Bove et al.1998; Jagger and Elsner 2006) so the network consisting of La Niña years has a higher betweenness centrality as more of the La Niña years have above normal frequency of hurricanes affecting the United States compared to the El Niño years. It also suggests that La Niña's influence on hurricanes is more transient (lasting for less time) than El Niño's influence, all else being the same.

The ENSO influence on hurricanes over the North Atlantic results from changes in thunderstorm patterns across the equatorial Pacific as the ocean temperatures change. With warm waters over the eastern equatorial Pacific during El Niño years, thunderstorms are more numerous resulting in upper level winds (16 km in altitude) that blow away from the thunderstorms and toward the tropical North Atlantic ocean. These high level winds tend to tear apart developing tropical cyclones over the Caribbean and central Atlantic resulting in fewer hurricanes affecting the United States. When the equatorial Pacific ocean cools during La Niña events the thunderstorm activity diminishes or ceases and so does the attendant shearing winds across the tropical Atlantic.

The results also show that the other climate variables do not appear to have a large influence on the network topology. The network diameter is largest for above normal NAO years and the maximum degree is lowest for below normal SST years.

Table 7.4: Visibility network properties conditioned three large scale climate conditions. Including the North Atlantic oscillation (NAO), Southern oscillation index (SOI), and Atlantic sea surface temperature (SST).

	NAO		SOI		SST	
	Above	Below	Above	Below	Above	Below
Max Deg.	24	26	26	26	23	20
Mean Deg.	6.3±0.48	6.3±0.52	6.6±0.55	7.2±0.69	6.6±0.56	6.4±0.49
Max Clos.	0.54	0.54	0.59	0.60	0.54	0.52
Mean Clos.	0.34±0.01	0.36±0.01	0.39±0.01	0.40±0.01	0.35±0.01	0.35±0.01
Max Betw.	1491	1425	894	557	1479	1160
Mean Betw.	78±27	75±26	58±21	53±14	75±23	73±23
Clustering Coeff.	0.52	0.50	0.51	0.55	0.53	0.52
Diameter	7	5	5	5	5	6

7.5 Summary

This chapter examined the time series of U.S. hurricanes from the perspective of network theory. An algorithm based on concepts from Lacasa (2008) uses the set of annual counts of hurricanes affecting the U.S. (1851–2008) to construct a temporal network termed the visibility network. This visibility network provided a way to identify which years are unique in terms of having many landfalls but surrounding in time by years with relatively few landfalls. Visibility networks were also constructed for regional hurricane activity these areas are the Gulf Coast, Florida, and the East Coast. Comparisons of the individual area's visibility network metrics reveals that visibility within the networks change depending on the area. The algorithm is also used to create six networks based on large scale climate variables.

The topological characteristics of each these networks were examined. Average degree (or average local centrality) for the visibility network (1851–2008) is 6.8. Closeness in the visibility network is the degree a year is directly visible to all other years in the network. It reflects the ability for one year to see through the network of years. Years with high frequencies of hurricane counts are able to see more years in the network. Overall the visibility network has few years with many lines of visibility, therefore, many linkages to other years. Years with high hurricane count have more visibility in the network than those years that have less storms. A year is more central if it is a link in more visibility chains between other years in the network. It was found that depending on which region (Gulf, Florida or East Coast) you are looking at the years that are central to the networks change. For instance the Gulf Coast years 1852, 1871, 1886 and 1964, are those with higher nodal connectivity. Where as for the East Coast network 1861, 1893, 1955 and 2004 have more local centrality in the visibility network. The Florida network matches the U.S. network in their mean topological characteristics. This indicates that even though the networks represent the same time frame, different years are more visible to other years dependent on the location. Results for the visibility networks conditioned on climate show that of the three climate variables considered, ENSO appears to have the greatest influence on the topology of the visibility network.

The next chapter will wrap up the dissertation by providing a summary of the finding and including some discussion on limitations and future work.

CHAPTER 8

SUMMARY, LIMITATIONS AND FUTURE DIRECTIONS

8.1 Summary

Hurricane activity has a profound affect on lives and property along the coast.Property damage in the United States averages in the billions of dollars annually (Pielke et al. 2008). Hence, the frequency and intensity of hurricanes is the topic of much of the current research. Much less work has been done toward understand the relationships of hurricanes across different regions and how these relationships change with climate factors. This dissertation addresses various relational aspects of hurricane activity through the application of network analysis.

Network analysis has been used in a variety of fields to study relational data, but has yet, until now, to be used in the study of hurricane climatology. The big conceptual hurdle was how to represent the set of hurricanes affecting the United States (or anywhere for that matter) as a network. The dissertation considers two different approaches to overcome this hurdle. The present work is largely expository introducing network analysis and showing how it can be applied to possibly better understanding regional hurricane activity. Results of this approach may provide risk managers with another tool to evaluate potential loss events.

This research was divided into two cases based on the approach for constructing the network. The first case consisted of networks developed based on the relationships of spatial locations of landfalls and the second case consisted of networks developed based on the relationships of the temporal occurrence of landfalls. In the first case, the network linked coastal locations (termed nodes) with particular hurricanes (termed links). The topology (structure) of the network was examined using various local and global metrics including degree, closeness, betweenness, diameter, and clustering coefficient. 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. Results showed that certain regions of the coast (like Louisiana) have high hurricane occurrence rates, but not necessarily high values of network connectivity. Low values of connectivity indicated that hurricanes affecting Louisiana tended not to affect other regions. 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. Thus this relational way of examining hurricanes provide different information not contained in the examining of regional frequency.

In the second case, the network linked the year-to-year variation in U.S. hurricane activity based on the notion of "visibility." The "visibility" network linked years experiencing hurricane landfalls with other hurricane landfall years "visible" to each other through time. The topological structure of the visibility network was again probed using various local and global metrics. It was found that years with high frequencies of hurricane counts are able to see more years in the network. A year is more central in the network if it is a link in more visibility chains between other years in the network. Overall the visibility network has few years with many lines of visibility, therefore, many linkages to other years.

The network structure dependent on whether the hurricane occurrence took place on the Gulf, Florida or East Coast is examined and it is found that depending on which area you are looking at, the years that are central to the networks change. Indicating that even though the networks represent the same time frame, different years are more visible to other years dependent on the location.

The question of how the topology changes with changing climate was considered by reconstructing networks based on three independent climate factors. Six conditional networks were constructed for the spatial and temporal networks based on years of below and above average values of these three important climate variables. It was found that the ENSO phenomenon in the equatorial Pacific had the most significant influence on both the hurricane and the visibility networks. The present work represents a first step toward understanding relational aspects of hurricane activity using networks and how those relationships changed under different climate scenarios. The broader impacts are an introduction of network analysis to hurricane climatology.

8.2 Limitations and Future Directions

This dissertation answered the question of how to create a network from a list of hurricane occurrences. However the two approaches taken resulted in undirected networks. That is, the links between nodes do not have a direction of relationship meaning the relationship is symmetric. Consider a hurricane that hits Florida before moving west and hitting Texas. In the above network analysis Texas and Florida are linked in an undirected way. However, since Florida gets hit first it might make sense to create a directed network where the link between Texas and Florida points in the direction of Texas. Similar analysis as was done on the undirected network could then be performed on the directed network with additional characteristics arising about the in and out-node linkages. However, the relatively small number of directed linkages may preclude an in-depth analysis using directed networks.

One way around the relatively small sample size of 158 years is to include older historical data in the analysis. Recent work by Chenoweth (2006) to collate historical archives of tropical cyclones in the western North Atlantic basin back to 1700 is particularly relevant in this regard. Perhaps better still is to include data from paleotempestology studies (Liu and Fearn 1993; Donnelly and Woodruff 2007). Paleotempestology is the study of prehistoric storms from geological and biological evidence. Coastal wetlands and lakes are subject to overwash events during hurricanes, when barrier sand dunes are overtopped by storm surge. A sediment core taken from the bottom of a near-coastal lake or marsh will record these episodic events as sand layers between the organic peat. As Liu (2007) points out, each record serves as a type of climate station. Connecting these various stations together using network analysis could help better understand the relationship between hurricanes and climate (Elsner 2007).

As mentioned in Chapter 4 two regions affected at least once over the period of record by the same hurricane results in a linkage. Information about how frequently this occurs is lost from the type of network analysis. Future research could consider links with various "strengths" depending on how often regions are both affected. The extra information provided by linkage strength would likely add to a better understanding of the hurricane network.

Another direction would be to build prediction models of network structure based on pre–season climate conditions. One way this could be achieved is using a Bayesian network (or a belief network). A Bayesian network (or a belief network) is a probabilistic graphical model that represents a set of variables and their probabilistic independencies. Because a Bayesian network is a complete model for the variables and their relationships, it can be used to answer probabilistic queries about them. For example, the network can be used to find out updated knowledge of the state of a subset of variables when other variables (the evidence variables) are observed. This process of computing the posterior distribution of variables given evidence is called probabilistic inference. The posterior gives a universal sufficient statistic for detection applications, when one wants to choose values for the variable subset which minimize some expected loss function, for instance the probability of decision error. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. In terms of the hurricane network given the landfall location, the network could be used to compute the probabilities of the same hurricane occurring in another location. For the visibility network given the visibility of one year, the network could be used to compute the probabilities of visibility in a future year.

Finally is would be possible to construct visibility networks from the covariate data including the NAO, SST, and ENSO. The structure of these networks could then be compared with the structural properties of the hurricane network. Then each of those network structures could then be examined using local and global metrics. This investigation may provide further insight into how the indices are intra related in addition to being compared and/or conditioned against/on one another.

APPENDIX A

UPDATED JARRELL ET AL. 1992 LIST

Chronological List of All Hurricanes which Affected the Continental United States: 1851-2005.(Updated from Jarrell et al. 1992 and reflecting official HURDAT reanalysis changes through 1914. Note that from 1915 through 1979, no official wind speed estimates are currently available. Document revised in May 2006)

Year	Sn	Month	States Affected and Category by States	Highest Saffir-Simpson U.S. Category	Central Pressure	Max. Winds	Name
1851	1	Jun	TX, C1	1	977 mb	80 kt	-----
1851	4	Aug	FL, NW3; IGA, 1	3	960	100	“Great Middle Florida”
1852		Aug	FL, SW1	1	977	80	-----
1852	1	Aug	AL, 3; MS, 3; LA, 2; FL,NW1,SW2	3	961	100	“Great Mobile”
1852	3	Sep	FL, SW1	1	985	70	-----
1852	5	Oct	FL, NW2; IGA, 1	2	969	90	“Middle Florida”
1853	8	Oct	* GA, 1	1	965	70	-----
1854	1	Jun	TX, S1	1	985	70	-----
1854	3	Sep	GA, 3; SC, 2; FL, NE1	3	950	100	“Great Carolina”
1854	4	Sep	TX, C2	2	969	90	“Matagorda”
1855	5	Sep	LA, 3; MS, 3	3	950	110	“Middle Gulf Shore”
1856	1	Aug	LA, 4	4	934	130	“Last Island”
1856	5	Aug	FL, NW2; IAL, 1; IGA, 1	2	969	90	“Southeastern States”
1857	2	Sep	& NC, 1	1	961	80	-----
1858	3	Sep	NY, 1; CT, 1; RI, 1; MA, 1	1	976	80	“New England”
1859	5	Sep	AL, 1; FL, NW1	1	985	70	-----
1860	1	Aug	LA, 3; MS, 3; AL, 2	3	950	110	-----
1860	4	Sep	LA, 2; MS, 2; AL, 1	2	969	90	-----
1860	6	Oct	LA, 2	2	969	90	-----
1861	2	Aug	* FL, SW1	1	970	70	“Key West”
1861	5	Sep	NC, 1	1	985	70	“Equinoctial”
1861	8	Nov	NC, 1	1	985	70	“Expedition”
1865	4	Sep	LA, 2; TX, N1	2	969	90	“Sabine River-Lake Calcasieu’
1865	7	Oct	FL, SW2; FL, SE1	2	969	90	-----
1866	1	Jul	TX, C2	2	969	90	-----
1867	1	Jun	SC, 1	1	985	70	-----
1867	7	Oct	LA, 2; TX, S1, N1; FL, NW1	2	969	90	“Galveston”
1869	2	Aug	TX, C2	2	969	90	“Lower Texas Coast”
1869	5	Sep	LA, 1	1	985	70	-----
1869	6	Sep	RI, 3; MA, 3; NY, 1; CT, 1	3	963	100	“Eastern New England”
1869	10	Oct	& ME, 2; MA, 1	2	965	90	“Saxby’s Gale”
1870	1	Jul	AL, 1	1	985	70	“Mobile”
1870	6	Oct	* FL, SW1, SE1	1	970	70	“Twin Key West (I)”
1870	9	Oct	FL, SW1	1	977	80	“Twin Key West (II)”
1871	3	Aug	FL, SE3, NE1, NW1	3	955	100	-----
1871	4	Aug	FL, SE2, NE1	2	965	90	-----
1871	6	Sep	FL, NW1; FL, SW1	1	985	70	-----
1873	3	Sep	FL, NW1	1	985	70	-----
1873	5	Oct	FL, SW3, SE2, NE1	3	959	100	-----
1874	6	Sep	FL, NW1; SC, 1; NC, 1	1	985	70	-----
1875	3	Sep	TX, C3, S2	3	960	100	-----
1876	2	Sep	NC, 1; VA, 1	1	980	80	-----
1876	5	Oct	FL, SW2, SE1	2	973	90	-----

1877	2	Sep	LA, 1; FL, NW1	1	985	70	-----
1877	4	Oct	FL, NW3; IGA, 1	3	960	100	-----
1878	5	Sep	FL, NW2, SW2, NE1; SC, 1; GA, 1	2	970	90	-----
1878	11	Oct	NC, 2; VA, 1; MD, 1; DE, 1; NJ, 1; IPA, 1	2	963	90	-----
1879	2	Aug	NC, 3; VA, 2; MA, 1	3	971	100	-----
1879	3	Aug	TX, N2; LA, 2	2	964	90	-----
1879	4	Sep	LA, 3	3	950	110	-----
1880	2	Aug	# TX, S3	3	931	110	-----
1880	4	Aug	FL, SE2, NE1, NW1	2	972	90	-----
1880	6	Sep	NC, 1	1	987	70	-----
1880	9	Oct	FL, NW1	1	985	70	-----
1881	5	Aug	GA, 2; SC, 1	2	970	90	-----
1881	6	Sep	NC, 2	2	975	90	-----
1882	2	Sep	FL, NW3; IAL, 1	3	949	100	-----
1882	3	Sep	LA, 2; TX, N1	2	969	90	-----
1882	6	Oct	FL, NW1	1	985	70	-----
1883	3	Sep	NC, 2; SC, 1	2	965	90	-----
1885	2	Aug	SC, 3; NC, 2; GA, 1; FL, NE1	3	953	100	-----
1886	1	Jun	TX, N2; LA, 2	2	973	85	-----
1886	2	Jun	FL, NW2; IGA, 1	2	973	85	-----
1886	3	Jun	FL, NW2; IGA, 1	2	973	85	-----
1886	4	Jul	FL, NW1	1	985	70	-----
1886	5	Aug	TX, C4	4	925	135	"Indianola"
1886	8	Sep	# TX, S1, C1	1	973	80	-----
1886	10	Oct	LA, 3; TX, N2	3	955	105	-----
1887	4	Jul	FL, NW1; IAL, 1	1	981	75	-----
1887	6	Aug	* NC, 1	1	946	65	-----
1887	9	Sep	TX, S2	2	973	85	-----
1887	13	Oct	LA, 1	1	981	75	-----
1888	1	Jun	TX, C1	1	985	70	-----
1888	3	Aug	FL, SE3, SW1; LA2	3	945	110	-----
1888		Sep	& MA, TS	TS	985	55	-----
1888	7	Oct	FL, NW2, NE1	2	970	95	-----
1889	6	Sep	LA, 1	1	985	70	-----
1891	1	Jul	TX, C1, N1	1	977	80	-----
1891	3	Aug	FL, SE1	1	985	70	-----
1893	4	Aug	NY, 1	1	986	75	"Midnight Storm"
1893	6	Aug	GA, 3; SC, 3; INC, 1; FL, NE1	3	954	100	"Sea Islands"
1893	8	Sep	LA, 2	2	973	85	-----
1893	10	Oct	LA, 4; MS, 2; AL, 2	4	948	115	"Chenier Caminanda"
1893	9	Oct	SC, 3; NC, 2; IVA, 1	3	955	105	-----
1894	4	Sep	FL, SW2, NE1; SC, 1; VA, 1	2	975	90	-----
1894	5	Oct	FL, NW3; IGA, 1; NY, 1; RI, 1	3	955	105	-----
1895	2	Aug	# TX, S1	1	973	65	-----
1896	1	Jul	FL, NW2	2	973	85	-----
1896	2	Sep	RI, 1; MA, 1	1	985	70	-----
1896	4	Sep	FL, NW3, NE3; GA, 2; SC, 1; INC, 1; IVA, 1	3	960	110	-----
1897	2	Sep	LA, 1; TX, N1	1	981	75	-----
1898	1	Aug	FL, NW1	1	985	70	-----
1898	2	Aug	GA, 1; SC, 1	1	980	75	-----
1898	7	Oct	GA, 4; FL, NE2	4	938	115	-----

1899	2	Aug	FL, NW2	2	979	85	-----
1899	3	Aug	NC, 3	3	945	105	-----
1899	8	Oct	NC, 2; SC, 2	2	955	95	-----
1900	1	Sep	TX, N4	4	936	125	"Galveston"
1901	3	Jul	NC, 1	1	983	70	-----
1901	4	Aug	LA, 1; MS, 1; AL, 1	1	973	80	-----
1903	3	Sep	FL, SE1, NW1	1	976	80	-----
1903	4	Sep	NJ, 1; DE, 1	1	990	70	-----
1904	2	Sep	SC, 1	1	985	70	-----
1904	3	Oct	FL, SE1	1	985	70	-----
1906	2	Jun	FL, SW1, SE1	1	979	75	-----
1906	5	Sep	SC, 1; NC, 1	1	977	80	-----
1906	6	Sep	MS, 2; AL, 2; FL, NW2; LA, 1	2	958	95	-----
1906	8	Oct	FL, SW3, SE3	3	953	105	-----
1908		May	&NC, TS	TS	989	55	-----
1908	3	Jul	NC, 1	1	985	70	-----
1909	2	Jun	TX, S2	2	972	85	-----
1909	4	Jul	TX, N3	3	959	100	"Velasco"
1909	6	Aug	# TX, S1	1	955	65	-----
1909	8	Sep	LA, 3; MS, 2	3	952	105	"Grand Isle"
1909	10	Oct	FL, SW3, SE3	3	957	100	-----
1910	3	Sep	TX, S2	2	965	95	-----
1910	5	Oct	FL, SW2	2	955	95	-----
1911	1	Aug	FL, NW1; AL,1	1	985	70	-----
1911	2	Aug	SC, 2; GA, 1	2	972	85	-----
1912	4	Sep	AL, 1; FL, NW1	1	988	65	-----
1912	6	Oct	TX, S2	2	973	85	-----
1913	1	Jun	TX, S1	1	988	65	-----
1913	4	Sep	NC, 1	1	976	75	-----
1913	5	Oct	SC, 1	1	989	65	-----
1915	1	Aug	FL, NE1				
1915	2	Aug	TX, N4,C1;LA, 1	4	945	-----	"Galveston"
1915	4	Sep	FL, NW1	1	988	-----	-----
1915	6	Sep	LA, 4;MS, 2;FL, NW2	4	931	-----	"New Orleans"
1916	2	Jul	MS, 3; AL, 3	3	948	-----	-----
1916		Jul	MA, 1	1	-----	-----	-----
1916	4	Jul	SC, 2	1	980	-----	-----
1916	6	Aug	TX, S4	3	948	-----	-----
1916	14	Oct	AL, 2; FL, NW2	2	972	-----	-----
1916		Nov	FL, SW1	1	-----	-----	-----
1917	4	Sep	FL, NW3	3	958	-----	-----
1918	1	Aug	LA, 3	3	955	-----	-----
1918	3	Aug	NC, 1				
1919	2	Sep	FL, SW4,SE2; TX, S3,C3	4	927	-----	-----
1920	2	Sep	LA, 2	2	975	-----	-----
1920	3	Sep	NC, 1	1	-----	-----	-----
1921	1	Jun	TX, C2	2	979	-----	-----
1921	6	Oct	FL, SW3, NE2	3	952	-----	"Tampa Bay"
1923	3	Oct	LA, 1	1	985	-----	-----
1924	4	Sep	FL, NW1	1	985	-----	-----
1924	7	Oct	FL, SW1	1	980	-----	-----
1925	2	No-De	FL, SW1	1	-----	-----	-----

1926	1	Jul	FL, NE2	2	967	-----	-----
1926	3	Aug	LA, 3	3	955	-----	-----
1926	6	Sep	FL, SE4, SW3, NW3; AL, 3	4	935	-----	“Great Miami”
1928	1	Aug	FL, SE2	2	-----	-----	-----
1928	4	Sep	FL, SE4, NE2; GA, 1; SC, 1	4	929	-----	“Lake Okeechobee”
1929	1	Jun	TX, C1	1	982	-----	-----
1929	2	Sep	FL, SE3, NW2	3	948	-----	-----
1932	2	Aug	TX, N4	4	941	-----	“Freeport”
1932	3	Sep	AL, 1	1	979	-----	-----
1933	5	Jl-Au #	TX, S2; FL, SE1	2	975	-----	-----
1933	8	Aug	NC, 2; VA, 2	2	971	-----	-----
1933	11	Sep	TX, S3	3	949	-----	-----
1933	12	Sep	FL, SE3	3	948	-----	-----
1933	13	Sep	NC, 3	3	957	-----	-----
1934	2	Jun	LA, 3	3	962	-----	-----
1934	3	Jul	TX, S2	2	975	-----	-----
1935	2	Sep	FL, SW5, NW2	5	892	-----	“Labor Day”
1935	6	Nov	FL, SE2	2	973	-----	-----
1936	3	Jun	TX, S1	1	987	-----	-----
1936	5	Jul	FL, NW3	3	964	-----	-----
1936	13	Sep	NC, 2	2	-----	-----	-----
1938	2	Aug	LA, 1	1	985	-----	-----
1938	4	Sep	NY, 3; CT, 3; RI, 3; MA, 3	3	946	-----	“New England”
1939	2	Aug	FL, SE1, NW1	1	985	-----	-----
1940	2	Aug	TX, N2; LA, 2	2	972	-----	-----
1940	3	Aug	GA, 2; SC, 2	2	970	-----	-----
1941	2	Sep	TX, N3	3	958	-----	-----
1941	5	Oct	FL, SE2, SW2, NW2	2	975	-----	-----
1942	1	Aug	TX, N1	1	992	-----	-----
1942	2	Aug	TX, C3	3	950	-----	-----
1943	1	Jul	TX, N2	2	969	-----	-----
1944	3	Aug	NC, 1	1	990	-----	-----
1944	7	Sep	NC, 3; VA, 3; NY, 3; CT, 3; RI, 3; MA, 2	3	947	-----	-----
1944	11	Oct	FL, SW3, NE2	3	962	-----	-----
1945	1	Jun	FL, NW1	1	985	-----	-----
1945	5	Aug	TX, C2	2	967	-----	-----
1945	9	Sep	FL, SE3	3	951	-----	-----
1946	5	Oct	FL, SW1	1	980	-----	-----
1947	3	Aug	TX, N1	1	992	-----	-----
1947	4	Sep	FL, SE4, SW2; MS, 3; LA, 3	4	940	-----	-----
1947	8	Oct	GA, 2; SC, 2; FL, SE1	2	974	-----	-----
1948	5	Sep	LA, 1	1	987	-----	-----
1948	7	Sep	FL, SW3, SE2	3	963	-----	-----
1948	8	Oct	FL, SE2	2	975	-----	-----
1949	1	Aug	* NC, 1	1	980	-----	-----
1949	2	Aug	FL, SE3	3	954	-----	-----
1949	10	Oct	TX, N2	2	972	-----	-----
1950	2	Aug	AL, 1	1	980	-----	Baker
1950	5	Sep	FL, NW3	3	958	-----	Easy
1950	11	Oct	FL, SE3	3	955	-----	King
1952	2	Aug	SC, 1	1	985	-----	Able

1953	2	Aug		NC, 1	1	987	-----	Barbara
1953	4	Sep		ME, 1	1	-----	-----	Carol
1953	8	Sep		FL, NW1	1	985	-----	Florence
1954	3	Aug		NY, 3; CT, 3; RI, 3; NC, 3	3	960	-----	Carol
1954	5	Sep		MA, 3; ME, 1	3	954	-----	Edna
1954	9	Oct		SC, 4; NC, 4; MD, 2	4	938	-----	Hazel
1955	2	Aug		NC, 3; VA, 1	3	962	-----	Connie
1955	3	Aug		NC, 1	1	987	-----	Diane
1955	9	Sep		NC, 3	3	960	-----	Ione
1956	7	Sep		LA, 2; FL, NW1	2	975	-----	Flossy
1957	2	Jun		TX, N4; LA, 4	4	945	-----	Audrey
1958	8	Sep		NC, 3				Helene
1959	4	Jul		SC, 1	1	993	-----	Cindy
1959	5	Jul		TX, N1	1	984	-----	Debra
1959	8	Sep		SC, 3	3	950	-----	Gracie
1960	5	Sep		FL, SW4; NC, 3; NY, 3; FL, NE2; CT, 2; RI, 2; MA, 1; NH, 1; ME, 1	4	930	-----	Donna
1960	6	Sep		MS, 1	1	981	-----	Ethel
1961	3	Sep		TX, C4	4	931	-----	Carla
1963	4	Sep		TX, N1	1	996	-----	Cindy
1964	5	Aug		FL, SE2	2	968	-----	Cleo
1964	6	Sep		FL, NE2	2	966	-----	Dora
1964	10	Oct		LA, 3	3	950	-----	Hilda
1964	11	Oct		FL, SW2, SE2	2	974	-----	Isbell
1965	3	Sep		FL, SE3; LA, 3	3	948	-----	Betsy
1966	1	Jun		FL, NW2	2	982	-----	Alma
1966	9	Oct		FL, SW1	1	983	-----	Inez
1967	2	Sep		TX, S3	3	950	-----	Beulah
1968	8	Oct		FL, NW2, NE1	2	977	-----	Gladys
1969	3	Aug		LA, 5; MS, 5	5	909	-----	Camille
1969	7	Sep		ME, 1	1	980	-----	Gerda
1970	3	Aug		TX, S3	3	945	-----	Celia
1971	6	Sep		LA, 2	2	978	-----	Edith
1971	7	Sep		TX, C1	1	979	-----	Fern
1971	8	Sep		NC, 1	1	995	-----	Ginger
1972	2	Jun		FL, NW1; NY, 1; CT, 1	1	980	-----	Agnes
1974	6	Sep		LA, 3	3	952	-----	Carmen
1975	5	Sep		FL, NW3; IAL, 1	3	955	-----	Eloise
1976	3	Aug		NY, 1	1	980	-----	Belle
1977	2	Sep		LA, 1	1	995	-----	Babe
1979	2	Jul		LA, 1	1	986	-----	Bob
1979	4	Sep		FL, SE2, NE2; GA, 2; SC, 2	2	970	-----	David
1979	6	Sep		AL, 3; MS, 3	3	946	-----	Frederic
1980	1	Aug		TX, S3	3	945	100	Allen
1983	1	Aug		TX, N3	3	962	100	Alicia
1984	5	Sep	*	NC, 3	3	949	100	Diana
1985	2	Jul		SC, 1	1	1002	65	Bob
1985	4	Aug		LA, 1	1	987	80	Danny
1985	5	Sep		AL, 3; MS, 3; FL, NW3	3	959	100	Elena
1985	7	Sep		NC, 3; NY,3; CT,2; NH,2; ME,1	3	942	90	Gloria
1985	10	Oct		LA, 1	1	971	75	Juan

1985	11	Nov	FL, NW2;IGA, 1	2	967	85	Kate
1986	2	Jun	TX, N1	1	990	75	Bonnie
1986	3	Aug	NC, 1	1	990	65	Charley
1987	7	Oct	FL, SW1	1	993	65	Floyd
1988	7	Sep	LA, 1	1	984	70	Florence
1989	3	Aug	TX, N1	1	986	70	Chantal
1989	8	Sep	SC, 4; INC, 1	4	934	120	Hugo
1989	10	Oct	TX, N1	1	983	75	Jerry
1991	2	Aug	RI, 2; MA, 2; NY, 2; CT, 2	2	962	90	Bob
1992	2	Aug	FL, SE5, SW4; LA, 3	5	922	145	Andrew
1993	5	Aug	* NC, 3	3	960	100	Emily
1995	5	Aug	FL, NW2, SE1	2	973	85	Erin
1995	15	Oct	FL, NW3; IAL, 1	3	942	100	Opal
1996	2	Jul	NC, 2	2	974	90	Bertha
1996	6	Sep	NC, 3	3	954	100	Fran
1997	5	Jul	LA, 1; AL, 1	1	984	70	Danny
1998	2	Aug	NC, 2	2	964	95	Bonnie
1998	5	Sep	FL, NW1	1	987	70	Earl
1998	7	Sep	FL, SW2; MS, 2	2	964	90	Georges
1999	2	Aug	TX, S3	3	951	100	Bret
1999	6	Sep	NC, 2	2	956	90	Floyd
1999	9	Oct	FL, SW1	1	987	70	Irene
2002	12	Oct	LA, 1	1	963	80	Lili
2003	3	Jul	TX, C1	1	979	80	Claudette
2003	9	Sep	NC, 2; VA, 1	2	957	90	Isabel
2004	1	Aug	* NC, 1	1	972	70	Alex
2004	3	Aug	FL, SW4, SE1, NE1; SC,1; NC,1	4	941	130	Charley
2004	6	Aug	SC, 1	1	985	65	Gaston
2004	7	Sep	FL, SE2, SW1	2	960	90	Frances
2004	9	Sep	AL, 3; FL, NW3	3	946	105	Ivan
2004	10	Sep	FL, SE3, SW1, NW1	3	950	105	Jeanne
2005	3	Jul	LA, 1	1	991	65	Cindy
2005	4	Jul	FL, NW3; IAL, 1	3	946	105	Dennis
2005	11	Aug	FL, SE1; LA, 3; MS, 3; AL, 1	3	920	110	Katrina
2005	15	Sep	* NC, 1	1	982	65	Ophelia
2005	17	Sep	FL, SW1; LA, 3; TX, N2	3	937	100	Rita
2005	22	Oct	FL, SW3; FL, SE2	3	950	105	Wilma
2007	8	Sep	TX, N1; LA, 1	1	985	80	Humberto
2008	4	Jul	TX, S2	2			Dolly
2008	7	Sep	LA, 3	3			Gustav
2008	9	Sep	TX, N2	2			Ike

Notes:

States Affected and Category by States Affected: The impact of the hurricane on individual U.S. states based upon the Saffir-Simpson Scale (through the estimate of the maximum sustained surface winds at each state). (TX S-South Texas, TX C-Central Texas, TX N-North Texas, LA-Louisiana, MS-Mississippi, AL-Alabama, FL NW-Northwest Florida, FL SW-Southwest Florida, FL SE-Southeast Florida, FL NE-Northeast Florida, GA-Georgia, SC-South Carolina, NC-North Carolina, VA-Virginia, MD-Maryland, DE-Delaware, NJ-New Jersey, NY-New York, PA-Pennsylvania, CT-Connecticut, RI-Rhode Island, MA-Massachusetts, NH-New Hampshire, ME-Maine. In Texas, south refers to the area from the Mexican border to Corpus Christi; central spans from north of Corpus Christi to Matagorda Bay and north refers to the region from north of Matagorda Bay to the Louisiana border. In Florida, the north-south dividing line is from Cape Canaveral [28.45N] to Tarpon Springs [28.17N]. The dividing line between west-east Florida goes from 82.69W at the north Florida border with Georgia, to Lake Okeechobee and due south along longitude 80.85W.)

Highest U.S. Saffir-Simpson Category: The highest Saffir-Simpson Hurricane Scale impact in the United States based upon estimated maximum sustained surface winds produced at the coast.

Central Pressure: The observed (or analyzed from peripheral pressure measurements) central pressure of the hurricane at landfall.

Maximum Winds: Estimated maximum sustained (1-min) surface (10 m) winds to occur along the U. S. coast. Winds are estimated to the nearest 10 kt for the period of 1851 to 1885 and to the nearest 5 kt for the period of 1886 to date. (1 kt = 1.15 mph.)

* - Indicates that the hurricane center did not make a U.S. landfall (or substantially weakened before making landfall), but did produce the indicated hurricane force winds over land. In this case, central pressure is given for the hurricane's point of closest approach.

& - Indicates that the hurricane center did make a direct landfall, but that the strongest winds likely remained offshore. Thus the winds indicated here are lower than in HURDAT.

- Indicates that the hurricane made landfall over Mexico, but also caused sustained hurricane force surface winds in Texas. The strongest winds at landfall impacted Mexico, while the weaker maximum sustained winds indicated here were conditions estimated to occur in Texas. Indicated central pressure given is that at Mexican landfall.

Additional Note: Because of the sparseness of towns and cities before 1900 in some coastal locations along the United States, the above list is not complete for all states. Before the Gulf of Mexico and Atlantic coasts became settled, hurricanes may have been underestimated in their intensity or missed completely for small-sized systems (i.e., 2004's Hurricane Charley). The following list provides estimated dates when accurate tropical cyclone records began for specified regions of the United States based upon U.S Census reports and other historical analyses. Years in parenthesis indicate possible starting dates for reliable records before the 1850s that may be available with additional research: Texas-south – 1880, Texas-central – 1851, Texas-north – 1860, Louisiana – 1880, Mississippi – 1851, Alabama < 1851 (1830), Florida-northwest – 1880, Florida-southwest – 1900, Florida-southeast – 1900, Florida-northeast – 1880, Georgia < 1851 (1800), South Carolina < 1851 (1760), North Carolina < 1851 (1760), Virginia < 1851 (1700), Maryland < 1851 (1760), Delaware < 1851 (1700), New Jersey < 1851 (1760), New York < 1851 (1700), Connecticut < 1851 (1660), Rhode Island < 1851 (1760), Massachusetts < 1851 (1660), New Hampshire < 1851 (1660), and Maine < 1851 (1790).

APPENDIX B

VISIBILITY CODE

Created by Thomas Jagger to construct the visibility network. The code is written in R.

```
`get.visibility` <-
function(y,x=1:length(y),size=Inf,sets=F)
{
#We assume that y and x are pairs, with x being the independent vector, and y the dependent vector
#We form slopes to each item and diffrerence the slopes from both sides to get the horizon.
#All points inside the horizen are kept.
#returns span. You can create the actual list from span as
#size: length to search in forward, back directions.
ly<-length(y)
ly1<-ly-1
tx<-x
ty<-y
val<-vector(mode="list",length=ly)
mss<-ly:2
if(size != Inf)
mss<-(size-mss)*(mss > size) + mss
for(i in 1:ly1)
 {
 ms<-mss[i]
 xx<-tx[2:ms]
 yy<-ty[2:ms]
 slopes<-(yy-ty[1])/(xx-tx[1])
 val[[i]]<-which(cummax(slopes)==slopes)+i
 tx<-tx[-1]
 ty<-ty[-1]
 }
  val.sparse<-cbind(row=rep(1:length(val),sapply(val,function(x) length(x))),col=unlist(val))
  val.sparse<-rbind(val.sparse,val.sparse[,c(2,1)])
  val.sparse<-val.sparse[order(val.sparse[,1]),]
  by.node<-split(val.sparse[,2],val.sparse[,1])
  k<-sapply(by.node,length)
  degree.dist<-table(k)
  degree.dist<-data.frame(k=as.numeric(names(degree.dist)),degree=as.vector(degree.dist))
  degree.dist<-cbind(degree.dist,P=degree.dist[,2]/ly)
  return(list(sm=val.sparse,node=by.node,pk=degree.dist))
}
```

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