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Visibility network of United States hurricanes

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[1] The authors demonstrate how to construct a network from a time series of U.S. hurricane counts and show how it can be used to identify unusual years in the record. The network links years based on a "line-of-sight" visibility algorithm applied to the time series plot and is physically related to the variation of hurricanes from one year to the next. The node degree is the number of links connected to a node. The authors find that the distribution of node degree is consistent with a random Poisson process. High hurricane-occurrence years that are surrounded by years with few hurricanes have many linkages. Of the environmental conditions known to affect coastal hurricane activity, they find years with little sunspot activity during September (peak month of the hurricane season) best correspond with the unusually high linkage years. **Citation:** Elsner, J. B., T. H. Jagger, and E. A. Fogarty (2009), Visibility network of United States hurricanes, *Geophys. Res. Lett.*, *36*, L16702, doi:10.1029/2009GL039129.

1. Introduction

[2] On average the continental United States gets hit by one or two hurricanes per year. The historical occurrences of hurricanes arriving at the coast have been studied in various ways [*Elsner and Kara*, 1999; *Lyons*, 2004; *Keim et al.*, 2007]. Most studies have focused on how hurricane frequency changes with various climate conditions [*Gray et al.*, 1993; *Lehmiller et al.*, 1997; *Bove et al.*, 1998; *Elsner and Jagger*, 2004, 2006; *Elsner et al.*, 2008]. Less work has been done to isolate and understand the anomalous years in the record. Here we examine the available historical record of U.S. hurricane counts using network analysis as a way to define anomalous years.

[3] Network analysis is the practical application of graph theory. Graph theory is the study of mathematical structures used in modeling pairwise relations between objects. Network analysis was recently introduced into climatology by *Tsonis et al.* [2006, 2007] and into hurricane climatology by *Fogarty et al.* [2009]. *Fogarty et al.* [2009] use networks to examine the region-to-region relationships of hurricanes affecting the United States.

[4] Here we use networks to examine year-to-year relationships in hurricane activity. This requires mapping the time series of hurricane counts onto a network. In this way the network is physically related to the variation of hurricanes from one year to the next. This idea is relatively new and was introduced by *Lacasa et al.* [2008]. In this paper we address the following two questions: How can the occurrence of hurricane landfalls over time be examined from the perspective of network analysis? And, what advantages are gained from this perspective? The intellectual merit of the work is an advance in our understanding of historical coastal hurricane activity and the broader impact is a new method for identifying anomalies from time series data.

2. Visibility Lines

[5] The time series of U.S. hurricane counts from 1851 through 1870 are shown as vertical bars in Figure 1. The data are taken from the U.S. National Oceanic and Atmospheric Administration (NOAA) chronological list of all hurricanes that have affected the continental United States (http://www.aoml.noaa.gov/hrd/hurdat/ushurrlist.htm). The bars form a discrete landscape across time. A bar is connected to another bar if it can "see" it. The "visibility" line represents a "line-of-sight" for the bar. Here we note that 1852 by virtue of its hurricane count can see 1851, 1853, 1854, 1860, 1861, and 1869, while 1851 can see only 1852. No lines cut through any bars. In this way each year in the time series is linked in a network.

[6] More formally let h_a be the hurricane count for year t_a and h_b the count for year t_b, then these two years are linked if for any other year t_i with count h_i

$$h_i \leq h_b + (h_a - h_b)\frac{t_b - t_i}{t_b - t_a} \quad (1)$$

By this definition each year is visible to at least its nearest neighbors (the year before and the year after), but not itself. The network is invariant under rescaling the horizontal or vertical axes of the time series as well as under horizontal and vertical translations [*Lacasa et al.*, 2008].

[7] In network parlance, years are nodes and the visibility lines are the links (or edges). The network shown in Figure 1 arises by releasing the years from chronological order and treating them as nodes linked by visibility lines. Here we see that 1869 is well connected while 1853 is not. Years featuring many hurricanes generally result in more links especially if neighboring years have relatively few hurricanes. This can be seen by comparing 1858 with 1866. Both years have only a single hurricane, but 1858 is adjacent to years that also have a single hurricane so it is linked to four other years. In contrast, 1866 is next to two years each with two hurricanes so it has the minimum number of two links. The degree of a node is the number of links connected to it.

[8] It is our contention that a network constructed from a time series of hurricane counts may reveal aspects of climatology not accessible with standard approaches. For instance, since the network preserves the properties of the time series, it is of interest to see if the network can detect the commonly assumed random Poisson process [*Elsner and Schmertmann*, 1993]. Also, are there anomalous years in the

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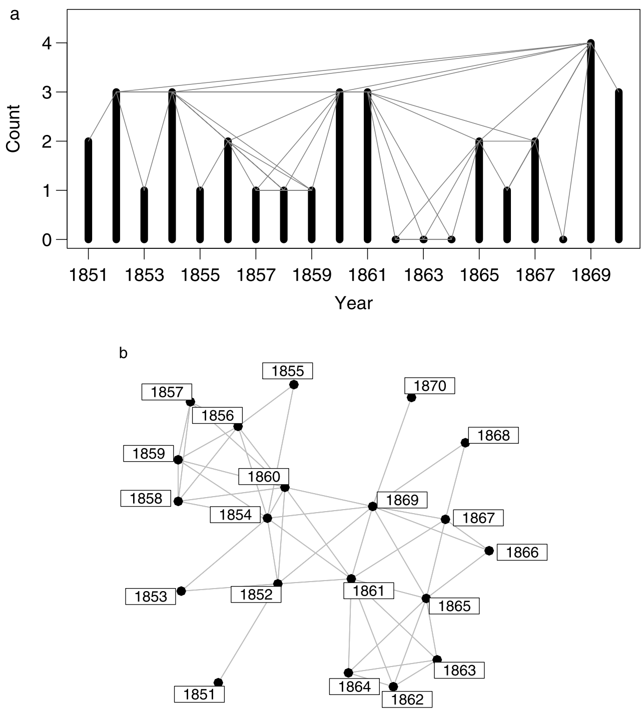

Figure 1. (a) Time series of U.S. hurricane counts from 1851–1870 with visibility lines drawn connecting the bars. (b) Network constructed from the visibility lines. The method is based on the work of *Lacasa et al.* [2008].

record that are not simply related to the number of hurricanes in that year, but also to the number of hurricanes in neighboring years? 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.

3. Visibility Network

[9] The mean number of U.S. hurricanes over the period from 1851–2008 is 1.8 hur/yr with a variance of 1.99 $(\text{hur/yr})^2$. Assuming an independent Poisson process, this indicates an 83% chance of at least one hurricane in a given year and a 11% chance of more than three. There is no significant upward or downward trend in the counts over the 158-year period [*Wang and Lee*, 2008]. The above definition of visibility is applied to the entire record of annual U.S. hurricane counts from the period 1851–2008 and the resulting network is plotted in Figure 2. The uncertainty associated with the exact hurricane count prior to 1899 is small for U.S. counts and has no substantive influence on the methodology or results presented here.

[10] The placement of years on the network plot is based on the simulated annealing method of *Kamada and Kawai* [1989] as implemented in the network package of R [*Butts et al.*, 2008]. Years with high degree are more likely to be found in dense sections of the network and these nodes are colored blue. Years with low degree (fewer links) are found near the perimeter of the network and are colored red.

[11] The year with the highest degree is 1985 with a total of 36 links. Two other years have 30 or more links including 1933 with 33 links and 1886 with 30 links. Other highly

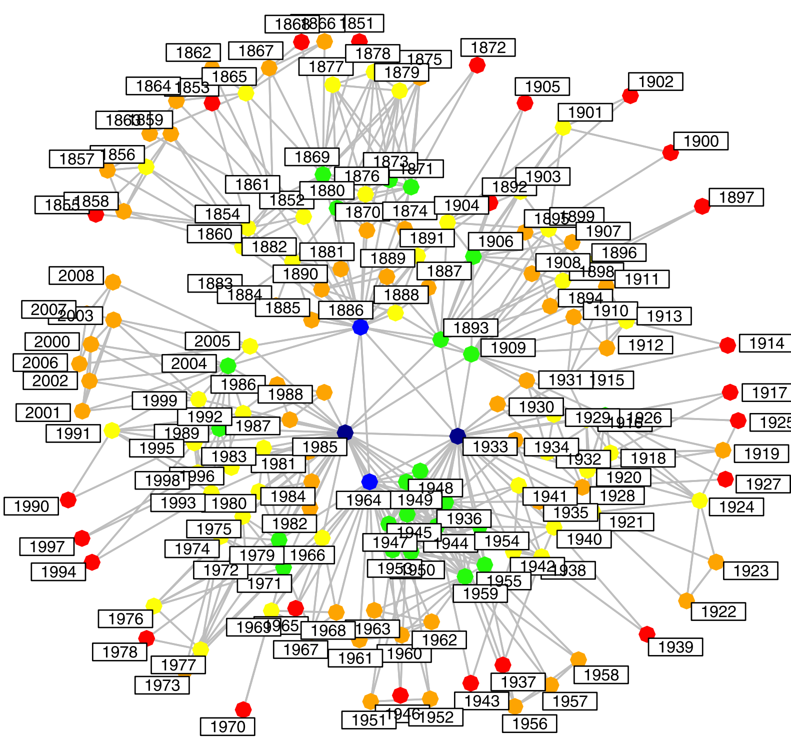

Figure 2. Visibility network of U.S. hurricanes. The network is based on the time series of U.S. hurricane counts over the period 1851–2008. The colors indicate the node degree (number of links); 2 or less (red), 3–5 (orange), 6–10 (yellow), 11–20 (green), 21–30 (blue), and more than 30 (dark blue).

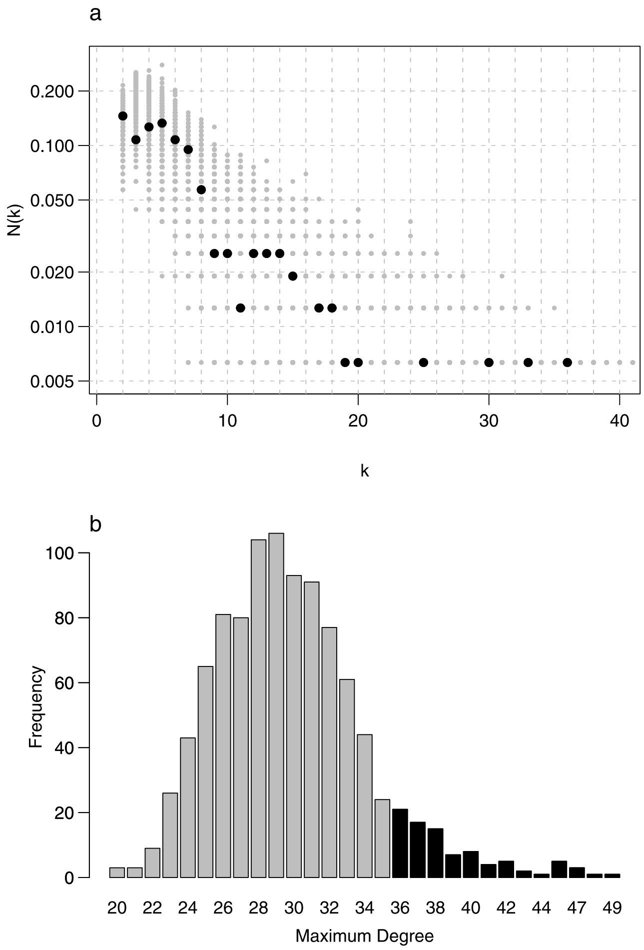

Figure 3. (a) Degree distribution of the network. $N(k)$ is the relative frequency of years with k links. The black dots are from the U.S. hurricane visibility network and the grey dots are from visibility networks created from 10^3 random Poisson draws of length 158. (b) Distribution of the maximum degree from 10^3 random Poisson draws. Less than 10% of the simulated networks have maximum degree of 36 or more (black bars).

connected years include 1964, 1936, and 1959 in that order. There is a noticeable group of years with relatively high degree in the 1940s. Recent years with a minimum of degrees include 1990, 1994, and 1997. The mean degree is 6.9 indicating that an average year is linked to about seven other years.

4. Degree Distribution and Anomalous Years

[12] The total number of degrees in the network is 1094 (sum over all node degrees). Since there are 158 nodes, twenty percent of the network consists of approximately 32 nodes. And the top twenty percent of the nodes account for 46% of the total number of degrees. The degree distribution is a plot of the relative frequency of nodes N with k degrees versus k (Figure 3).

[13] The black dots show the degree distribution of the visibility network on a semi-log plot. Most years have relatively few links but a few years have many links. The grey dots show the range of degree distributions based on 10^3 visibility networks constructed from random Poisson time series of length 158 and mean rate of 1.8 yr^{-1}. For a given number of links (k) the number of years with that many links varies considerably. On average, years at the beginning and end of the time series will have lower degree. The largest value of k for the visibility network is 36 links and only 10% of the simulated series have that k value or larger. Since hurricane activity along the U.S. coast is mediated by various environmental signals [*Elsner and Jagger*, 2008] the counts from the observed record follow a Poisson distribution with a bit of over-dispersion.

[14] It is important to note that the above analysis shows that the degree distribution does not deviate significantly from the degree distribution of a Poisson time series. Interestingly, however, it suggests a novel way to think about anomalies in a time series. The years are anomalous not in a statistical sense of violating a Poisson assumption, but in the sense that the temporal ordering of the counts identifies a year that is unique in that it has a large count but is surrounded in time by years with low counts. Thus we contend that node degree is a useful indicator of an anomalous year. That is, a year that stands above most of the other years, but particularly above its "neighboring" years represents more of an anomaly in physical terms than does a year that is simply well-above the average. Node degree captures information about the frequency of hurricanes for a given year and information about the relationship of that frequency to the frequencies over the given year's recent history and near future. With this definition 1985 stands out as the most anomalous of the hurricane years with 1933, 1886, and 1964 also unusual.

[15] The relationship between node degree and the annual hurricane count is tight, but not exact. Years with a low number of hurricanes are ones that are not well connected to other years, while years with an above normal number are ones that are more connected on average. The Spearman rank correlation between year degree and year count is 0.75 with a p value less than 0.001 as evidence in support of the hypothesis of no correlation. But this is largely a result of low count years. The correlation drops to 0.32 (p value of 0.034) when considering only years with more than two hurricanes. Thus high count is necessary but not sufficient for characterizing the year as anomalous, as perhaps it should be.

5. Linkage to Climate

[16] Having defined and identified the anomalous hurricane years, we seek an explanation for their unusualness. The frequency of U.S. hurricanes is modulated by North Atlantic sea-surface temperature (SST) as an indicator of ocean heat content, the El Niño-Southern Oscillation (ENSO) cycle as an indicator of shear, the North Atlantic oscillation (NAO) as an indicator of steering currents, and the solar cycle as an indicator of upper atmosphere temperature [*Elsner and Jagger*, 2008]. Here we examine index values for these variables corresponding to the anomalous years. It should be noted that there are may be additional climate factors (like the Atlantic Multidecadal Mode) that modulate hurricane activity but are not considered here because of the limited data needed to describe such factors.

[17] June values of the NAO and September values of the Southern Oscillation Index (SOI) are obtained from the

Table 1. Unusual Hurricane Years[a]

Rank	Degree	Year	Count	SST (Sep)	SOI (Sep)	NAO (Jun)	SSN (Sep)
1	36	1985	6	−0.41	+0.02	−0.54	−1.09
2	33	1933	5	+0.96	+0.19	−0.93	−1.07
3	30	1886	7	−0.50	+1.25	−0.62	−0.73
4	25	1964	4	−0.58	+1.26	−1.10	−1.07

[a]Years with anomalous U.S. hurricane activity and corresponding covariate values. Anomalies are defined using the node degree (Degree) of the visibility network. Count is the number of hurricanes that made U.S. landfall. Covariate values including Atlantic sea-surface temperature (SST), the Southern Oscillation Index (SOI), the North Atlantic Oscillation (NAO) and sunspot number (SSN) have units of standard deviation. The month over which the values are averaged is given in parentheses.

Climatic Research Unit of the University of East Anglia. September values of North Atlantic SST are obtained from NOAA and September sunspot numbers produced by the Solar Influences Data Analysis Center (SIDC), World Data Center for the Sunspot Index, at the Royal Observatory of Belgium are obtained from NOAA.

[18] Table 1 lists the top four anomalous years as identified by node degree in the visibility network together with the corresponding climate conditions during the hurricane season. To aid comparisons, the variables are scaled to have a mean of zero and a standard deviation of one over the period of record for the particular month. Therefore the values in the table are in units of standard deviation.

[19] In general, the four anomalous years can be described as years with cooler ocean temperatures (lower SST values), La Niña conditions (positive SOI values), negative NAO conditions, and fewer sunspot. The mean departure from normal over the top four anomalous years is largest for the SSN (−1 sd) followed by the NAO (−0.8 sd) and the SOI (+0.7 sd). The smallest mean departure occurs with SST (−0.1 sd). The September sunspot number averaged over the entire period 1851–2008 is 52.8 compared with 8.8 averaged over the four most unusual years (a reduction of 83% from the mean). The probability that in a record of 158 independent years four years picked at random would all have sunspot numbers less than about 22 (anomaly less than or equal to −0.73) is slightly less than 0.6%. This compares with a probability of 0.9% for the standardized NAO June values all less than or equal to −0.54 and 7% for the standardized SOI values all greater than +0.02. Since the method essentially defines anomalously high activity in periods of low activity, it is not surprising that the SOI, which tracks the hurricane-inhibiting El Niño years, does not distinguish the network nodes as well as the SSN and the NAO.

[20] The perspective afforded by the network topology provides new insights. While ocean warmth is important for increasing the probability of coastal hurricanes, ocean temperature varies slowly from year to year so corresponding high frequency years tend to cluster in time leading to a lower node degree compared with isolated high frequency years. In contrast, a ‘‘cooler’’ sun (fewer SSN) increases the probability of coastal hurricanes, but this affect is through changes in stratospheric ozone and upper troposphere temperature [*Elsner and Jagger*, 2008], which changes more rapidly from month to month. Thus an extended period of near (or below) normal ocean temperature is punctuated by a year with many coastal hurricanes resulting from cooler tropopause temperatures. The isolated, high hurricane occurrence year results in a high node degree in the visibility network. A similar, but less forceful, argument can be made with the NAO.

6. Conclusion

[21] This paper addressed the following two questions: How can the occurrence of hurricane landfalls over time be examined from the perspective of network analysis? And, what advantages are gained from this perspective? We answer the first question by constructing a visibility network using the method described by *Lacasa et al.* [2008] on annual counts. The visibility network links a year to another year by a straight line on the time series graph such that the line does not intersect any year's hurricane count bar. The number of links from a given year is the year's node degree. We show that the degree distribution of the set of all years is consistent with a random Poisson process, however the largest node contains a somewhat unusual number of links.

[22] To answer the second question we contend that node degree is a useful metric of anomalous years. The network identifies years that are unique in terms of having many landfalls but surrounded in time by years with relatively few landfalls. Years with the highest node degree are considered anomalies; these include 1985, 1933, 1886, and 1964.

[23] Climate variables known to have a physical and statistical relationship to hurricane activity are examined during the anomalous years. Of the four variables, the anomalous years identify SSN as being the most unusual with all four years having a SSN that is about one standard deviation below the average. A set of years featuring near to slightly below normal ocean temperatures can be punctuated by a year with many coastal hurricanes resulting from lower tropopause temperatures caused by less ultraviolet radiation from a ‘‘cooler’’ sun [*Elsner and Jagger*, 2008]. The isolated high hurricane occurrence year results in a high node degree in the visibility network.

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