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Keywords

Disasters, Hurricane Katrina, emergent multiorganizational networks, interorganizational collaboration

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1 Introduction

When the impact of a natural or anthropogenic hazard (such as an earthquake, hurricane, or flood) exceeds the short-term capacity of human systems to respond, the result is a disaster. Disasters thus produce a “breaching” of the conventional patterns of social organization, leading to new (and sometimes long-lasting) social structures. In the modern context, one facet of this reorganization is the mobilization (and, in some cases, formation *ex nihilo*) of organizations to respond to the adverse event. In the aftermath of the initial impact, large numbers of organizations may converge upon the affected area, joined eventually by new organizations that are synthesized to solve particular problems or exploit particular assets arising during the response process (Fritz and Mathewson, 1957; Drabek and McEntire, 2002). Although some such entities will act more or less autonomously, many will collaborate in order to pool resources, resolve task interdependencies, or leverage complementary capabilities. The result of these interactions is an emergent multiorganizational network (or “EMON”), the evolving structure of realized relations among responding organizations.

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Although mass convergence of organizations in response to disaster is known to be ubiquitous in the developed world (see, e.g. Fritz and Mathewson, 1957; Mileti et al., 1975; Auf der Heide, 1989; Drabek and McEntire, 2002; Drabek, 2003), there are relatively few studies that examine the networks formed by these organizations in quantitative detail. Drabek et al. (1981) conducted an early comparative study of communication-based EMONs from remote area search and rescue operations, most of which arose from relatively small-scale events. Work by Topper and Carley (1999) examined collaboration among organizations in the Exxon Valdez disaster, with a particular focus on the dynamics of centrality over the course of the response. More recent work by Tierney (2003); Tierney and Trainor (2004); Comfort and Kapucu (2006) and Kapucu (2006) has examined the large collection of organizations responding to the World Trade Center disaster, an event that prompted substantial organizational interaction on a number of fronts; local newspaper coverage of organizational interactions during the Hurricane Katrina disaster has also been studied by Comfort and Haas (2006), with Lind et al. (2008) examining communication networks within two impacted communities. Although these studies vary considerably in coverage and methodology, all reinforce the basic intuitions that response networks involve a wide range of organizational actors (varying in scale, mission, and type); responding organizations differ considerably in the nature and extent of their interaction with others; and response networks show substantial change over time. Drabek et al. (1981) further note the relationship of structural position to influence in decision making processes, an argument that echoes a common theme within the social network literature (Gould and Fernandez, 1989; van Merode et al., 2004). Even in the absence of a formal command structure, however, collaborative relationships between responding organizations can act as critical conduits for information, resources, and logistical support (Auf der Heide, 1989; Drabek and McEntire, 2002; Wachtendorf, 2004).

This phenomenon of interorganizational collaboration is of particular importance for an event such as the 2005 Hurricane Katrina disaster, in which massive damage on a large spatial scale required a highly distributed response. A brief review of the storm's history (based on Knabb et al. (2005)) makes clear the extent of the challenges involved. Katrina formed from Tropical Depression 12 on 8/23/05¹ off the southeastern coast of Florida (near the Bahamas). It obtained hurricane status on 8/24/05, making its initial landfall in Florida on 8/25/05. The storm was relatively weak during this period, and damage was thus fairly limited. After crossing southern Florida, Katrina entered the Gulf of Mexico. There, it gained considerable strength, becoming a category 5 hurricane on the Saffir-Simpson scale by 8/28/05. Although the storm subsequently weakened, it was still a category 3 storm (with sustained winds of over 205kph, and hurricane winds over a 190km radius) when it made secondary landfall near Buras-Triumph, Louisiana on the morning of 8/29/05 (refer to Figure 1 based on NOAA (2006)). In addition to high winds, driving rain and a massive storm surge (over 8m in some locales) caused extensive flooding over large areas of coastal Louisiana, Mississippi, Alabama, and northwestern Florida. Damage in many areas was severe. Estimates of fatalities range from 1,319 (Bourque et al., 2006) to 1,833 (Knabb et al., 2005) persons, with approximately 2,500 persons reported missing (Bourque et al., 2006) and over 270,000 evacuees displaced (Gabe et al., 2006); the direct financial cost of the storm has been estimated at over \$80 billion (Knabb et al., 2005). Consonant with this grim picture, transportation and telecommunications infrastructures were severely degraded over much of the impacted region. Communities such as St. Bernard Parish, Louisiana were without telephone service for several weeks, and were without wireless telephony for several days (Banipal, 2006; Comfort and Haas, 2006). Such losses made an already complex response effort more difficult by reducing the ability of organizations to deploy to and operate within the affected area (Independent Panel Reviewing

¹For brevity, all dates are given in month/day/year format.



Figure 1: The Path and Strength of Hurricane Katrina, by Date

the Impact of Hurricane Katrina on Communications Networks, 2006). Despite these challenges, a large number of organizations from around the United States (and, in some cases, other countries) mobilized in response to the disaster. In the days following landfall, these organizations began undertaking relief efforts both individually and in collaboration with one another. The network of ties that developed between responding organizations serves as an important example of the formation of social structure in a substantially disrupted setting; by reconstructing this network, we thereby avail ourselves of a valuable opportunity to examine the structural context in which the initial stages of response to a large-scale disaster take place.

In this paper, then, we examine the dynamic network of interorganizational collaboration that emerged in response to the impact of Hurricane Katrina. Our study relies on archival materials collected from a number of institutional sources, which detail organizations' internal accounts of their and others' interactions. We begin our presentation with a discussion of these materials, as well as a brief description of our data coding methods. From this, we proceed to an overview of the data, as well as an exploratory analysis of the EMON's evolution, an identification of organizations that emerged as central actors in the response, and an investigation of the cohesive subgroups of collaborating organizations that formed within the broader network. Finally, we conclude with a discussion of several issues related to the use of archival methods in research on disaster-generated EMONs, and the use of automated methods for network extraction. The data set employed in this study is included as an appendix to this paper.

2 Data Collection and Coding

A major challenge in the study of interorganizational network formation during disaster is the identification of participating organizations (and ties among them) within a substantially disrupted setting. While direct observation of organizational behavior in the impacted area is rarely feasible on a large scale (particularly in the initial phases of an event), organizational activities leave durable traces that can be used to reconstruct the history of an event. In our case, these “traces” are archival materials produced by organizations involved in the response process, which describe activities taken by various actors (including but not limited to the issuing organizations) in the aftermath of the storm. As we shall describe, the particular materials used here were documents produced to help coordinate task performance by organizational members and affiliates involved in the response effort, and belong to a fairly standard genre of such documents. By using such task-centered, “backstage” materials (in the sense of Goffman (1959)), we avoid many of the potential biases associated with materials produced for outside entities. In this section, we describe the process of material collection and processing for this study, as well as the coding methods employed to extract network information from the source materials; further details. Some additional issues related to the use of these materials in disaster research are also discussed in Section 4.

2.1 Materials Collection and Document Processing

The source materials for this data set are drawn from a larger corpus of online documents manually collected by the authors during the period from 9/3/05 through 11/28/05. All information is derived from public sources. Here, we provide an overview of the general process of materials collection for this project, followed by a discussion of document processing and selection. Due to the dearth of “standard” procedures for the collection and processing of interorganizational network data from online documents, we describe our process in greater detail than might be typical for an article using more conventional data collection methods.² It is hoped that this will serve to facilitate replication, extension, and improvement of this methodology by others in the field.

2.1.1 Collection

The authors collected materials for this project by searching online sources for documents related to the Hurricane Katrina response. Sources were identified by multiple methods, including: use of commercial search engines (e.g., Google); direct browsing of state, local, and federal web sites (as well as sites of other organizations identified as potential responders); references to web sites in online discussion groups, mailing lists, or web-based information portals; and suggestions from practitioners in the emergency management community. Where possible, a census of potential sources (e.g., all state-level emergency management web sites) was employed. This process was continued throughout the data collection period, as many potential information sources did not become mobilized until some days following the initial impact; as explained below, the date of source acquisition did not generally affect the data that was obtainable from that source. In this paper we henceforth refer to those organizations from which these materials were obtained as “source organizations.”

Data collection was performed by a manual inspection of and information retrieval from all source web sites. This process was conducted daily from 9/3/05 through 11/1/05, with one additional round of collection on 11/28/05. (Note that most documented response activities closed down before or shortly after 11/1/05, making this a fairly natural termination point.) With very

²Additional details are provided in the data set documentation; see appendix.

Type	Count
City Governments	5
County Governments	20
State Agencies	4
State Governments	13
Federal Entities	16
Other Organizations	5
Total	63

Table 1: Breakdown of Source Organizations by Type

few exceptions, information on response activities was posted on organizational web sites in a cumulative fashion; thus, most documents posted prior to the onset of data collection on 9/3/05 were still available on that day, and were captured by the collection process. Collection of documents was conducted approximately every 24 hours during the “daily” period, usually around midnight Pacific time. Given the static nature of the data (and in contrast with highly dynamic sources, such as weblogs (see, e.g. Butts and Cross, 2009)), collection for these materials was not sensitive to exact timing.

Materials collected consisted of situation reports, press releases, maps, advisories, and other substantive material posted to the web site of each source. Attempts were made to gather any informational material pertaining either to Katrina, or to any subsequent disaster to which the source was responding (e.g., Hurricane Rita). In some cases, materials were missing due to non-posting by the original source, or problems with the source web site (e.g., malformed URLs that could not be manually corrected). All accessible materials, however, were collected.

A tabulation of source organizations by type is shown in Table 1. There are 63 source organizations, headquartered in 14 states (including the District of Columbia). In Table 1, we distinguish between state governments and state agencies. State emergency management/homeland security offices and/or governor’s offices are considered to represent the state government *per se*, with “state agencies” consisting of other subordinate state-level entities not included in the former. Only the state of Arkansas was covered by a subordinate state-agency and not the state government *sui generis*. All told, the number of documents collected from the 63 source organizations is approximately 4,500.

It should be noted that an important advantage of the manual approach to data collection utilized here (as opposed to automated information retrieval, e.g., via “spiders” (Kobayashi and Takeda, 2000)) is its robustness to site design changes and human error on the part of the source organizations. We found that web sites were frequently reorganized during the collection period, with informational postings changing in location and occasionally in form. Similarly, file names and URLs were occasionally misspelled, misdated, or otherwise malformed, requiring manual correction to ensure correct retrieval. Although easily resolved by experienced human users, such inconsistencies made automated information retrieval impractical in this setting; this issue (which has implications for future research of this kind) will be revisited in Section 4.3.

2.1.2 Document Processing and Selection

For purposes of the current study, a smaller set of documents has been extracted from the larger corpus. Our objective in employing this subset is to restrict attention to a more manageable set of documents that cover organizational interaction during the initial phase of the Hurricane Katrina

response. From the full corpus, we thus restrict attention to materials covering events in the period from 8/23/05 through 9/5/05; this interval begins with the first mobilization in response to Katrina’s imminent landfall in Florida, and extends through the first seven days following landfall in Louisiana. In examining the materials within this set, we found that the vast majority of readily usable information was contained with a particular genre of documents known as *situation reports* (or “SITREPs”). SITREPs are extensively employed by responding organizations as a mechanism for rapidly summarizing ambient environmental conditions, ongoing hazards, losses incurred, and tasks being performed both by the issuing organization and by other organizations involved in the response process. These documents are issued on a periodic basis, and conventionally specify the time period for which the conditions indicated in the report apply—this makes them particularly useful when reconstructing the history of the Katrina response. Although typically prepared for internal use, SITREPs are frequently disseminated to other interested parties (including members of the public) who may be concerned with response activities and/or conditions in the immediate area. SITREPs are nearly always prepared in accordance with an internal format or template, and as such the SITREPs issued by a given entity tend to be constant in form; as organizations within the emergency management community use very similar standards for SITREP preparation, documents issued by different entities are also comparable in form and content. Because of their comparability, ubiquity, consistency, and well-defined temporal coverage, our current study focuses on these materials. Restricting the set of documents to SITREPs (or equivalent materials) with coverage in the selected time interval yields a subset of 187 documents; this set is employed for the analyses that follow.

Once the finalized set of documents was established, various metadata for the documents were accumulated and recorded. For each of the 187 documents, where available, we extracted the source organization that created the document, the publication date of the document, and the start and end dates of coverage.

2.2 Organizational Coding

The first step in the network extraction process is the identification of organizations referred to within the source materials. For this study, an “organization” is defined to be any named entity that represents (directly or indirectly) multiple persons or other entities, and that acts as a *de facto* decision making unit within the context of the response. This includes conventional organizational units such as non-profit corporations, firms, government agencies, teams, and representatives/liasons of such organizations, as well as emergent collectives such as emergency support function (ESF) groups and organized volunteer coalitions. It should be emphasized here that the distinguishing feature of an organizational actor for this study was its capacity to act as a decision maker. Thus, entities such as locations (e.g., airfields) would not be considered eligible for inclusion if they were merely passive sites for the action of others (e.g., simply a location for aircraft takeoffs/landings). On the other hand, an organization associated with such an entity with the capacity to act as a decision making unit (e.g., an airport management authority) would be considered eligible for inclusion in this data set. By the same token, sub-organizations acting as *de facto* decision making units in the field would be considered eligible for independent inclusion, regardless of whether or not their “parent” organizations were also present. This reflects the phenomenal nature of the response environment, in which multiple elements of a large-scale organization (e.g., the Federal Emergency Management Agency (FEMA)) frequently serve as semi-autonomous sources of action. Although this phenomenon is especially prevalent in disasters, it is not unique to this context; for instance, similar properties have been ascribed to “network forms” of organizations in entrepreneurial contexts such as the information and biotechnology industries (Powell, 1990; Powell

et al., 1996).

To improve the speed and accuracy of organizational identification, a two-stage process was used. In the first pass, a coder identified apparent textual references to eligible organizations (per the above definition); these references were tagged for subsequent examination. After this process was complete, a second pass was performed to code the tagged references (i.e., to associate the tagged text with a standardized organization name). Finally, standardized names were cross-checked to ensure consistency and correctness. In all, 1,577 eligible organizations were identified as having been present within the processed source materials.

2.3 Relational Coding

After the identification of organizational references, the next step in the network extraction process is the identification of collaborative relationships among organizations. For purposes of this project, two organizations are said to collaborate if they engage in any substantive interaction—e.g., information transfer, exchange of manpower, donations of material or financial support, or delegation of authority—related to task performance. As the directionality of such interactions was not uniformly apparent from the documentary evidence (and, in any event, would not be well-defined for all types of interaction), collaboration was coded as an undirected relation. Likewise, the documentary evidence did not always specify the full details of the collaborative relationship; for this reason, no distinction was made among different types of possible collaboration. Thus, collaboration for the present study is (by construction) a dyadic, mutual, and dichotomous relationship on the set of eligible organizations.

The process by which relationships were identified was similar to that employed for identifying organizations. As before, a two-pass procedure was used. In the first pass, a coder tagged all apparent references to relational activity between organizations within the source text. That is, all portions of text that indicated relational information between actors were flagged. In the second pass, these relational activity tags were inspected. All explicit mentions of relations between organizations referred to in the tagged text were extracted and aggregated into a master sociomatrix of organizations.

2.4 Acquisition of Secondary Data

In addition to the primary data on organizational interaction provided by the source materials, secondary information on organizational attributes was collected from other sources. The variables coded for each organization include: type (government, non-profit, for-profit, or collective), scale (ranging from local to international), parent organizations (if any), city and state location of the organization’s permanent headquarters (if applicable), and whether or not the organization was also a data source. The latter was self-evident from our SITREPs. The authors collected all other secondary data from information found on organizational websites. When a website could not be found, information about the organization’s city and state location was obtained by querying Internet search engines with the organization name and any other identifying information available in the SITREPs (the name of an organizational representative, for example). The specific procedures for collecting secondary data on organization type, scale, and parent hierarchy is described below.

2.4.1 Coding for Organizational “Lineage”

As noted above, *de facto* organizational actors within the Katrina response were often formally instantiated as sub-units of other, larger organizations. Such subordinate units are said to be “child” organizations, with the superordinate unit being referred to as the organization’s “parent.”

To facilitate reconstruction of the hierarchy in which particular actors were embedded, parental relationships were coded for all organizations in the Katrina EMON. In some cases, parent organizations were entities that appeared elsewhere in the data set (e.g. the U.S. Department of Defense is an organization found in the EMON but also is a parent of the United States Navy). In other cases, however, parent organizations were not themselves direct actors in the response (e.g. Choice Hotels, Inc., parent of Comfort Inn, Memphis, TN); lineage was traced in the same manner, regardless of EMON participation. Once all parent organizations for the 1,577 responding organizations were identified, this process was repeated on the parent set. Such iteration was continued until no new parent organizations could be identified; in some cases, this resulted in a chain of as many as five elements. For example, the U.S. Army Corps of Engineers Deployable Tactical Operations Center is a child of the U.S. Army Corps of Engineers (first order), which is a child of the U.S. Army (second order), which is a child of the U.S. Department of Defense (third order), which is a child of the U.S. Federal Government (fourth order). While such long chains were possible, not all organizations were identified to have parents. (Emergent organizations in the sense of Dynes (1970), for instance, do not have such relationships.) This structure of containment is a potentially useful adjunct to the information on organizational collaboration derived from the source documents. In particular, such information allows for flexible aggregation of low-level interactions when necessary, without imposing this constraint at the level of data collection.

To obtain this organizational lineage, information was first sought from child organization websites; relationships obtained in this way were then verified by inspection of the alleged parent organizations' websites. This approach yielded reliable results in all but a few cases, for which the protocol was reversed (i.e., suspected parents were searched to identify references to child organizations). In the case of for-profit entities, some child organizations' websites did not clearly indicate their parents. When this occurred, the organization name was queried through Internet search engines and a potential parent organization website was identified. Company prospectus sheets and other legal documents, usually available electronically, were used to verify child organizations by name and city and/or state location. In the case of Kerr-McGee Chemical LLC., for instance, the information that its parent was Anadarko Petroleum Corporation was determined through secondary source legal proceedings of the EPA vs. Anadarko Petroleum Corporation because the child company did not have an active website or listed phone number. All lineage information included within the Katrina data set reflect the organizations' respective relationships during the study period.

2.4.2 Scale/Type Coding

Two coders made several independent passes through the extracted data to acquire organizational type and scale of operations information for each organization in the Katrina EMON. The protocol for coding this data was based on the Tierney (2003) type and scale definitions for their 9/11 World Trade Center EMON study. Organizational scale—the size of the primary jurisdiction and/or region of operations for a given organization—was ascertained by examining organization names for cues about their area of focus and verifying the cues by examining supplemental information on organization websites, government documents, and SITREPs. The categories of organization scale are: local (15.7%), city (5.7%), county (10%), state (38%), interstate (1.3%), regional (2.9%), national (17.1%), and international (8.3%). Organizations with indeterminate scale were coded as missing on this dimension (missing $N = 17$, or 1.1% of the EMON). Where ambiguous, various Internet services such as organization websites, Google, and Wikipedia were referenced to acquire such information.

Organization type—the general terms under which an organization is chartered—was deter-

mined by examining the organization’s identity, and the identity of its parents when appropriate, for cues about the type, as well as by verifying cues available through supplemental information as above. In some cases, specialized databases (such as the airport information service <http://www.airnav.com/>) were also employed. Categories of organization type include: government (65.4%), collective (2.7%), not-for-profit (16.7%), and for-profit (13.6%). Type could not be ascertained for 26 organizations (1.6% of the EMON); these were coded as missing.

3 The Katrina EMON

After tagging and coding, our data consists of a set of 187 networks, each consisting of the organizations and associated relationships reported in a specific source document, as well as secondary information on the organizations involved. This information can be combined in a variety of ways to study the global network of interorganizational collaboration that emerged during and after the passage of Hurricane Katrina. Here, we explore several facets of the Katrina EMON data: the distribution of reports among information sources; the growth and development of the EMON over time; aggregate properties of the EMON structure; the emergence of certain organizations as central actors in the collaboration network; and the presence of cohesive subgroups within the aggregate structure.

3.1 Sources and Reporting

Table 2 displays basic descriptives for the portion of the Katrina EMON extracted from each of the 21 source organizations in this data set.³ Each network described in Table 2 consists of the organizations and collaborative relationships reported by a single source, aggregated over all SITREPs from that source. As the table indicates, there is substantial variation in the number of organizations mentioned by each source. Not surprisingly, those source organizations reporting on the largest number of other organizations, such as the Alabama Emergency Management Agency (alema), the Florida Department of Emergency Management (fldem), and the United States Office of Electricity Delivery and Energy Reliability (usea), were all organizations whose geographic jurisdictions were positioned along the storm track. Sources also showed substantial variation in the number of ties reported among mentioned organizations. Despite this, the vast majority of sources did note the existence of collaborative relationships: Palm Beach County, FL DEM (flpalmbe), Williamson County, TN EMA (tnwillia), and the National Interagency Fire Center (usnifc) were the only source organizations reporting no ties among mentioned organizations for the period studied here.

While many organizations are identified as active in the response, it is important to distinguish between *mobilization* and *collaboration*. An organization may be mobilized in the sense that it is actively involved in response activities (and thus present in the network), without those activities requiring direct collaboration with other organizations. Indeed, as Table 2 indicates, 15 of the 21 source organizations (about 71%) provided reports in which 50% or more of the involved organizations were isolates. That is, informant accounts consistently suggest the collaborating organizations are a minority of those active in the immediate post-impact period.

As we shall see, these “local” impressions continue to hold when individual source accounts are aggregated to estimate the global network. It is also evident that the size of the largest component within the activities reported on by each source varies greatly – some sources focus on network activities within a single component, whereas others report activities spanning many components. Table 3 displays the distribution of the types of organizations reported on by each

³See Appendix A for the full names of the source organizations.

Source Organization	Mentioned Organizations	Mentioned Ties	Proportion Isolates	Size of Largest Component
alema	275	83	0.78	0.2
avma	120	72	0.62	0.32
codem	72	88	0.29	0.68
fldem	271	146	0.63	0.29
fpalmbe	23	0	1	0.04
gagmag	8	5	0.38	0.62
gaohs	252	150	0.62	0.29
humane	43	26	0.49	0.47
iafc	25	9	0.64	0.36
mnhsem	43	35	0.33	0.67
mosema	50	46	0.24	0.72
msforres	12	3	0.58	0.25
twillia	8	0	1	0.12
txdem	79	71	0.24	0.59
txftbend	32	5	0.78	0.16
txgalves	20	1	0.9	0.1
usea	209	55	0.79	0.16
usihs	121	13	0.87	0.06
usnifc	46	0	1	0.02
usnps	123	48	0.63	0.32
vadem	64	26	0.61	0.31

Table 2: Aggregate Subnetworks Reported by Each Source Organization

source organization. We will return to some of these issues in Section 4.1, when we consider their implications for assessing the role of source organizations in the Katrina EMON.

3.2 Structural Evolution

As previously noted, an important dimension of the Hurricane Katrina EMON is its evolution through time. The SITREPs from which these network data were extracted span the entire study period, up to and including one week after landfall of Katrina in Louisiana, yielding thirteen daily “snapshots” (8/24/05 through 9/05/05). Examining the state of the EMON at each of these time points allows us to explore the evolution of social structure among the responding organizations. Some basic properties of these temporal cross sections are shown in Figure 2 and Table 4. As both clearly demonstrate, the data indicate substantial growth as time progresses.

Over time we see the emergence of a giant component within the network, joined by a large number of isolates and small non-isolate components. This giant component grows from only two organizations on 8/24/05 to 163 by 9/05/05 (reaching a maximum observed size of 219 organizations on 9/04/05). While the giant component grows over time, the number of smaller, non-isolate components increases on average as well. Substantively, this implies not only the formation of one central cluster of activity among the organizations in the Katrina response, but also the simultaneous proliferation of smaller clusters of organized activity. These smaller clusters often consist of organizations involved in similar fields.

The growth of the network as a whole is also readily seen in Figure 2, with an average accumulation of just under 60 organizations per day throughout the period (mean 58.8, SD 74.9). By the end of the observation period, over 700 organizations are reported as active on any given day. While this growth is accompanied by a small increase in mean degree, the increase is fairly modest once the first day is omitted ($p = 0.06$, one-tailed permutation test of correlation). A point of even greater stability is the fraction of isolates in the graph, a number whose decline is not significant ($p = 0.274$) even when the first time point is included ($p = 0.06$). Although the EMON expands by a factor of over 50 during the period of observation, the fraction of isolates within the structure generally fluctuates around a mean of 67.34% (SD 0.07, dropping to 0.05 with the first day omitted). Both of these factors suggest that while mass convergence to the scene is substantial, the propensity to become involved in collaborative activities remains roughly constant as the disaster unfolds. This, in turn, suggests the action of some equilibrating process, in which organizations balance the immediate returns to so-called “freelancing” activities (response operations conducted in isolation) with the costs and benefits of collaboration. For those that do collaborate, the coalescence of such efforts into a giant component is not in and of itself surprising in light of what would be expected from random mixing (Bollobás, 2001). Thus, a key feature of Katrina’s EMON evolution would seem to be (at first blush) the selection of organizations into or out of collaborative relationships *per se*, rather than simply the choice of with whom to collaborate.

3.3 Aggregate Network Structure

While the Katrina EMON can be considered intertemporally, it is also useful to examine the aggregate patterns of collaboration that develop over the course of the entire observation period. In addition to removing idiosyncratic variability due to the effects of day-to-day conditions, an aggregate view of the EMON provides an effective summary of the response as a whole, and as such may be more useful for detecting broader structural tendencies. Here, we highlight several properties of the aggregate network structure, before turning to the identification of central actors in the Katrina response network.

Source Organization	Government	Collective	Not-For-Profit	For-Profit	Unknown
alema	0.53	0.01	0.32	0.11	0.02
avma	0.43	0.02	0.39	0.13	0.02
codem	0.85	0.01	0.08	0.06	0
fdem	0.72	0.05	0.09	0.12	0.01
fpalmbe	0.87	0	0.04	0.09	0
gagmag	0.75	0.25	0	0	0
gaohs	0.71	0.06	0.19	0.04	0
humane	0.37	0.02	0.56	0.05	0
iafc	0.44	0.04	0.04	0.08	0.4
mnhsem	0.74	0.02	0.14	0.09	0
mosema	0.8	0.02	0.12	0.06	0
msforres	1	0	0	0	0
tnwillia	0.75	0	0.25	0	0
txdem	0.85	0	0.08	0.05	0.03
txftbend	0.34	0	0.66	0	0
txgalves	0.35	0	0.6	0.05	0
usea	0.37	0.01	0.05	0.57	0
usihs	0.78	0	0.12	0.11	0
usnifc	0.96	0.02	0.02	0	0
usnps	0.91	0	0.04	0.05	0
vadem	0.86	0.02	0.08	0.03	0.02

Table 3: Proportional Breakdown of Types of Mentioned Organizations by Source Organization

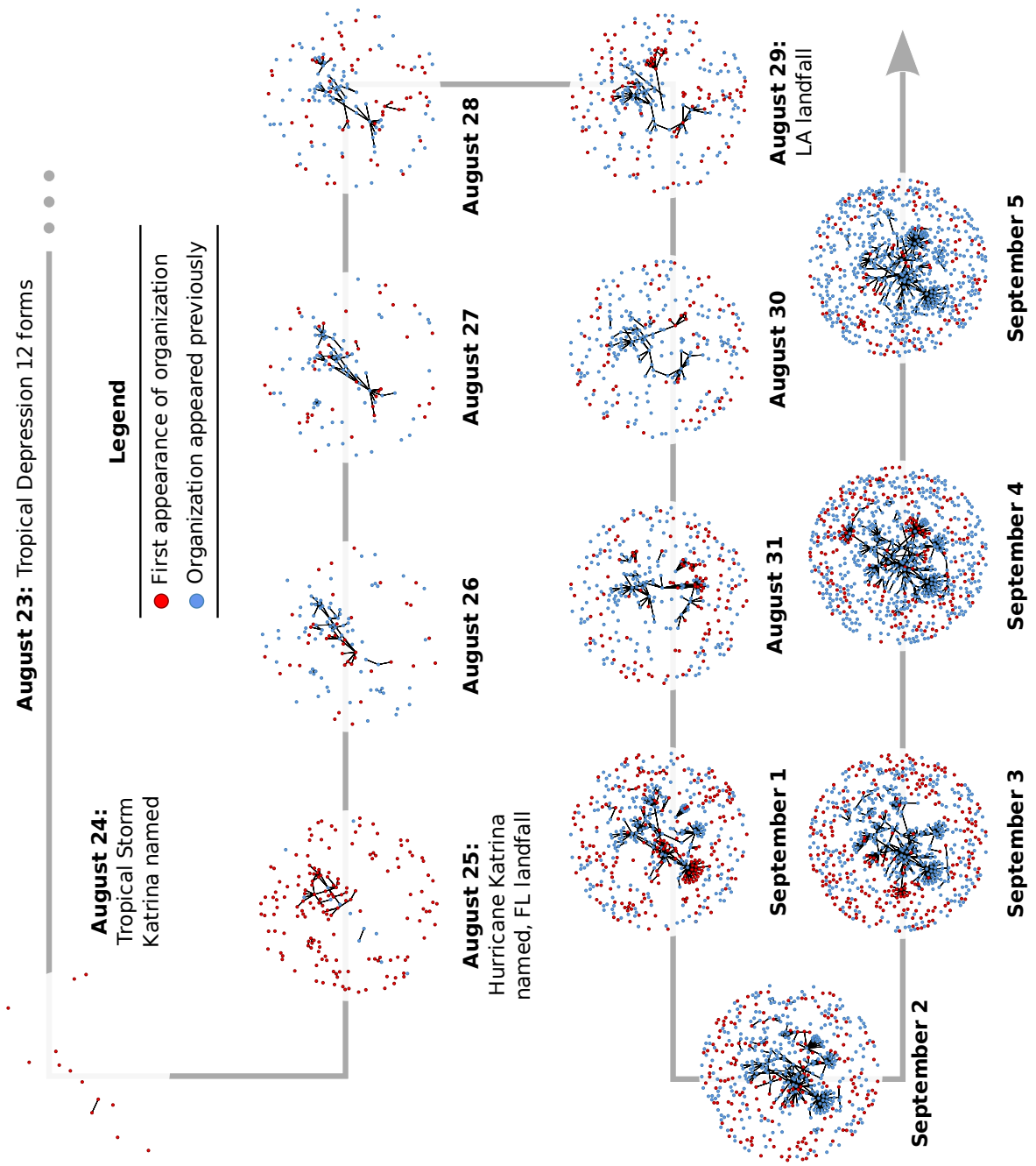


Figure 2: Katrina EMON Dynamics, August 24 through September 5, 2005

Date	Organizations	Ties	Mean Degree	% Isolates	Non-Isolate Components	Max. Component Size
08/24/05	13	1	0.15	84.62	1	2
08/25/05	169	47	0.56	69.23	11	21
08/26/05	118	42	0.71	63.56	6	26
08/27/05	124	50	0.81	58.06	7	15
08/28/05	154	40	0.52	68.83	8	11
08/29/05	265	77	0.58	70.19	9	42
08/30/05	275	63	0.46	76.36	11	22
08/31/05	332	122	0.73	70.18	13	47
09/01/05	489	224	0.92	62.17	19	121
09/02/05	533	225	0.84	60.6	22	98
09/03/05	673	288	0.86	62.26	29	133
09/04/05	775	312	0.81	63.48	20	219
09/05/05	719	264	0.73	65.92	28	163

Table 4: Katrina EMON Dynamics by Date

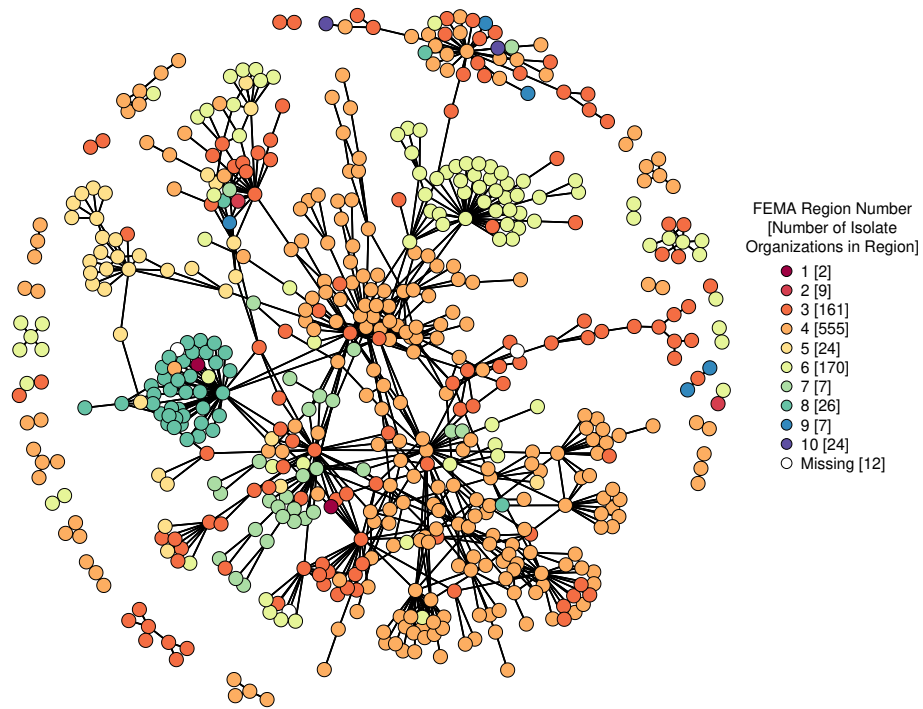


Figure 3: Aggregate Katrina EMON; Vertices Colored by FEMA Region of Organizational Headquarters

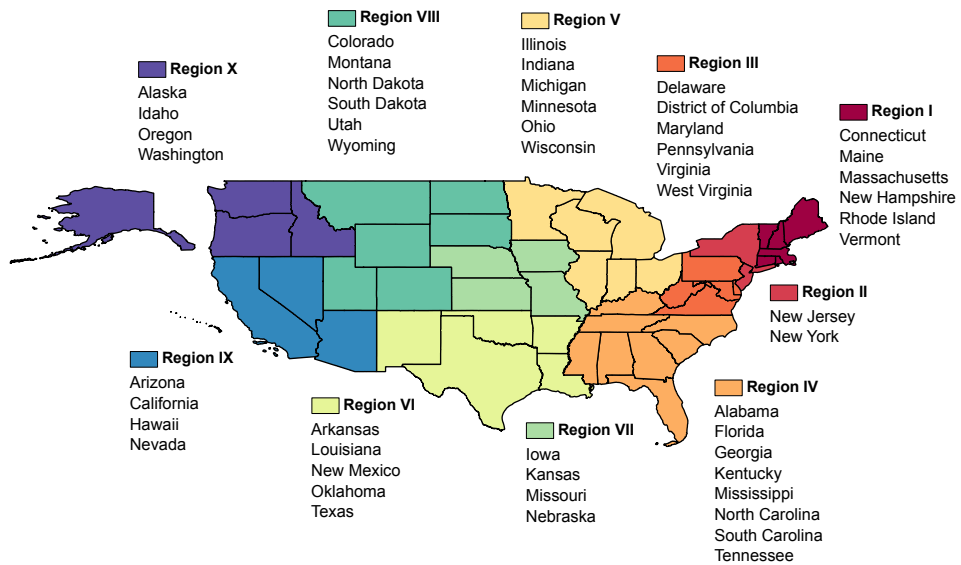


Figure 4: The 10 U.S. FEMA Regions, by State

To form an aggregate structure, the daily EMON “snapshots” were aggregated across each day using a union rule: that is, all vertices and edges reported in each day of data collection were combined into an aggregate graph. The resulting aggregated EMON is both large and sparse, with 1,577 vertices, 857 edges, 997 isolates, 26 non-isolate components, and a mean degree of approximately 1.1 (density 0.001). The sociogram of the aggregated EMON is displayed in Figure 3.

To provide a geographical context for the aggregate network structure, the vertices of Figure 3 are colored by membership in the regional divisions used by FEMA to coordinate emergency response activities within the United States. (Isolates are not shown, but counts within each region are provided in the figure legend.) The ten FEMA regions are themselves depicted in Figure 4. For purposes of analysis, we treat an organization as “belonging” to a FEMA region if its headquarters resides within it; FEMA regions are institutionally significant focal points for both pre- and post-event coordination within the emergency management community, and as such form a natural basis on which to divide the vertex set. As expected, there is considerable propinquity in the Katrina EMON both within and between FEMA regions. Of the edges in the aggregate network, 71.2% are incident between nodes that are in the same FEMA region ($p < 1e-08$, one-tailed Binomial test). A test of differential homophily by region (not shown) confirms that these strong propinquity effects are consistent across regions; interestingly, regions 4 and 6 (the two most directly affected by the storm) show slightly lower rates of self-mixing than other FEMA regions. An ERGM analysis shows that this difference does not persist when controls for regional average degree are added, suggesting that the effect stems from a general suppression of collaboration rates among organizations sited in the hardest hit areas, rather than from a reduction in propinquity *per se*.

In addition to the obvious propinquity in the aggregate EMON structure, Figure 3 suggests substantial heterogeneity in collaboration rates across organizations. While the mean degree of the aggregate EMON is approximately 1, the observed maximum of 45 (and mode of 0) confirms the presence of a very right-skewed degree distribution. Inspection of the degree distribution histogram reveals (Figure 5, solid dots) that the distribution is monotonic, but cannot effectively distinguish among competing models. Following Jones and Handcock (2003), we employ likelihood-based model selection criteria to assess the aggregate degree distribution. Poisson, geometric, negative binomial, Yule, and Waring distributions were fit to the aggregate degree data using the `degreenet` package of the `statnet` network analysis library (Handcock et al., 2003). Expected degree frequencies for each fitted model are depicted via the colored lines in the left panel of Figure 5. Goodness of fit information for these models is shown in Table 5; as the table indicates, the Waring and Yule models are clearly favored by the data. Fits for the latter two models are essentially similar (see also figure 5, right-hand panel), with the Bayesian information criterion favoring the Yule model and the corrected Akaike’s criterion slightly favoring the Waring model—since the Yule is a special case of the Waring model, this suggests that the degree distribution is effectively Yule-like in character. Such a result is interesting, given that the Yule/Waring distribution declines as a power law in the upper tail. Here, the MLE for the scaling parameter (under the Waring parametrization) is 3.09 ± 0.35 (asymptotic 95% CI), placing it almost exactly at the threshold of 3 required to exhibit finite variance. Simon (1955) famously demonstrated the potential for such distributions to arise via a frequency-biased sampling process, re-interpreted in the network context in terms of a “cumulative advantage” (Price, 1976) or “preferential attachment” (Barabási and Albert, 1999) mechanism. While many social structures (e.g., any with non-monotone degree distributions) cannot be accounted for in this way, we observe that the aggregate degree distribution for the Katrina EMON is not immediately incompatible with such a process. Alternately, distributions of this form can also arise as a consequence of unobserved heterogeneity; see, e.g., Irwin (1963), Johnson et al. (1992, chapter 6) for less context-specific discussion.

In addition to the degree distribution, we also examine a number of properties related to other

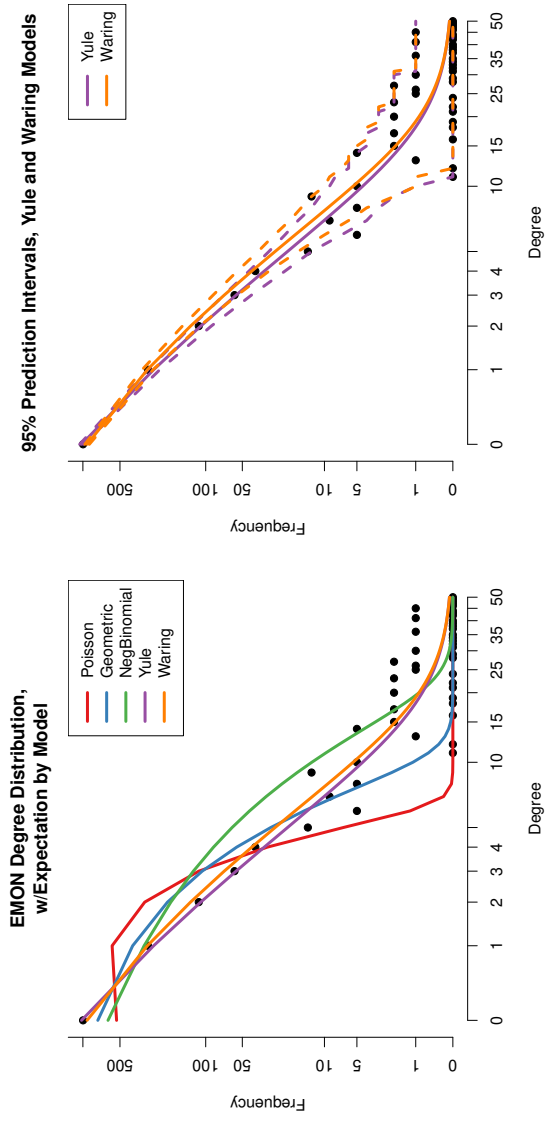


Figure 5: Katrina EMON Aggregate Degree Distribution, with Fitted Models

Model	df	Log Likelihood	AICC	BIC
Poisson	1	-3470.83	6943.67	6949.03
Geometric	1	-2278.29	4558.59	4563.95
Negative Binomial	2	-2072.55	4149.1	4159.82
Yule	1	-2035.11	4072.22	4077.59
Waring	2	-2033.78	4071.56	4082.28

Table 5: Degree Distribution Model Fits, Aggregate EMON Data

Graph Level Index	Observed	Mean	SD	Pr($X \leq$ Obs)	Pr($X \geq$ Obs)
	GLI	Random GLI	Random GLI		
Degree Centralization	0.028	0.003	0.000 ^b	1.000 ^a	0.000 ^b
Eigenvector Centralization	0.364	0.482	0.056	0.036	0.964
Krackhardt Efficiency	0.995	0.983	0.01	0.983	0.017
Proportion Isolates	0.632	0.337	0.008	1.000 ^a	0.000 ^b
Transitivity	0.160	0.001	0.002	1.000 ^a	0.000 ^b

^a $x < 1e - 3$; ^b $x > 0.999$

Table 6: Conditional Uniform Graph Test Results for Graph Level Indices

aspects of the EMON as a whole. Four graph level indices (GLIs) computed on the aggregate EMON were compared to GLI distributions from 1,000 randomly generated density-conditioned graphs to evaluate the extent to which the empirical network GLIs deviate from a baseline model of random association (Mayhew, 1984), i.e. a conditional uniform graph test. The GLIs tested for this purpose are degree centralization, eigenvector centralization, Krackhardt efficiency (Krackhardt, 1994), proportion of isolates, and transitivity, each of which summarizes some aspect of the global structure of the Katrina EMON. The results of this analysis are given in Table 6.

As reported in Table 6, the Katrina EMON has observed values greater than the 97.5% quantile of the baseline distributions in all cases other than eigenvector centralization. Degree centralization, proportion isolates, and transitivity are all highly significant with GLI values that are approximately 53, 35, and 103 standard deviations above the mean of the baseline distributions, respectively. Krackhardt efficiency is significantly high, despite being only 1.2 standard deviations above its expectation.⁴ The eigenvector centralization of the Katrina EMON is also significantly lower than expected at approximately 2.1 standard deviations below the mean of the baseline distribution (although the p -value in this case indicates much less deviation).

Together, these results provide evidence that the sparseness of the network is non-uniformly distributed. In particular, compared to random graphs of the same density, edges within the aggregate network are concentrated within a highly centralized giant component that—although sparse—does have far more triangles than would occur naturally. Although this lowers the Krackhardt efficiency somewhat, a small number of excess ties within a single large component (surrounded primarily by isolates) has less impact on the efficiency score than would the same number of excess ties spread among several much smaller components; thus, we observe an efficiency that is higher than that expected under the baseline model. The unexpectedly low level of eigenvector centralization further tells us that the excess edges in the giant component are not sufficiently concentrated to create the degree of core-periphery structure that would otherwise arise from density alone. While degree is quite inequitably distributed, therefore, we do not see strong evidence of a structurally dominant

⁴Note that its baseline distribution is highly non-Gaussian.

clique of mutually collaborating organizations—instead, the giant component is substantially heterogeneous, with a richer collection of interacting subgroups than would obtain from chance alone. As we will see in Section 3.5, this phenomenon arises from the presence in several sets of intensively collaborating organizations linked to one another by a combination of interdependencies and existing institutional relationships.

3.4 Central Organizations

As we have seen, the Katrina EMON is highly centralized with respect to degree, with most organizations acting alone and a small number participating in extensive collaboration. Likewise, the apparent concentration of triangles within an irregular inner core (a matter to which we return below) suggests that some organizations will be much better positioned to act in bridging roles than others. This invites the question of *which* organizations occupy the high-centrality positions within the aggregate network. Such organizations are expected to play key roles in the response process—with accompanying unique challenges. High degree organizations, for instance, are “mass collaborators.” Since collaborating with a new partner always entails coordination costs (Williamson, 1975), such mass collaborators are expected to face substantial pressure to systematize their interactions with other organizations. If effective, adaptations undertaken for this purpose may spread to partnering organizations, and thence to other portions of the network.

Unlike mass collaborators, high betweenness organizations may not have many partners; however, they must bridge portions of the collaboration network that are not otherwise well-connected. Given the limited communication infrastructure available in the aftermath of the storm (Lind et al., 2008), direct collaboration can be expected to have played a more significant role in propagating information and resources during the Katrina response than would be expected under normal conditions. While not all communication was restricted to collaborative relationships—and not all paths within the aggregate EMON would have been communication permeable (e.g., due to ordering effects, communication failure, etc.)—we may regard the aggregate network structure as at least a crude indicator of those pairs of organizations having the greatest opportunity for information and resource exchange during the early days of the response. To the extent that this is the case, organizations with high betweenness in the aggregate network are particularly likely to have been in a position to maintain contact between groups of organizations not otherwise able to share information or resources. Under the same assumptions, we may expect high-closeness organizations to end up obtaining novel information more quickly than their peers. This may, in turn, prompt such organizations to assume the role of “clearinghouses,” a role that is also facilitated by their structural positions. Thus, different dimensions of centrality in the network of interorganizational collaboration are expected to correlate with differing challenges and opportunities, leading to distinct patterns of behavior.

Turning to the data, we begin our analysis with degree, followed by betweenness and closeness centrality (Freeman, 1979). The degrees of the responding organizations range from 0 to 45, with the mean at 1.1 and the median at 0. As we have seen (and as Figure 6 illustrates), a small number of organizations collaborate with far more partners than is typical for the network as a whole. An enumeration of the ten highest-degree actors is given in Table 7 (see also Figure 6).

Considering Table 7, we observe that organizations having considerable prior experience with disasters and/or with advanced disaster preparedness measures and infrastructure in place tend to dominate the list of high-degree actors. That the American Red Cross maintains high numbers of collaborations aligns well with both the organization’s institutional status as an officially recognized coordinator of relief activities and its substantial infrastructure for supporting such coordination. High levels of disaster recovery experience, funding, and support are reasonable indicators that

Organization Name	Degree
Colorado Division of Emergency Management (DEM)	45
American Red Cross	41
Texas State Operations Center	36
U.S. Federal Emergency Management Agency (FEMA)	30
Emergency Management Assistance Compact	27
Georgia State Operations Center	27
Dry Tortugas/Everglades National Park	26
Florida SERT, Emergency Support Service Branch	25
Alabama EMA, Emergency Operations Center, ESF 9	23
Missouri Emergency Management Agency (EMA)	23

Table 7: Ten Highest Degree Central Organizations

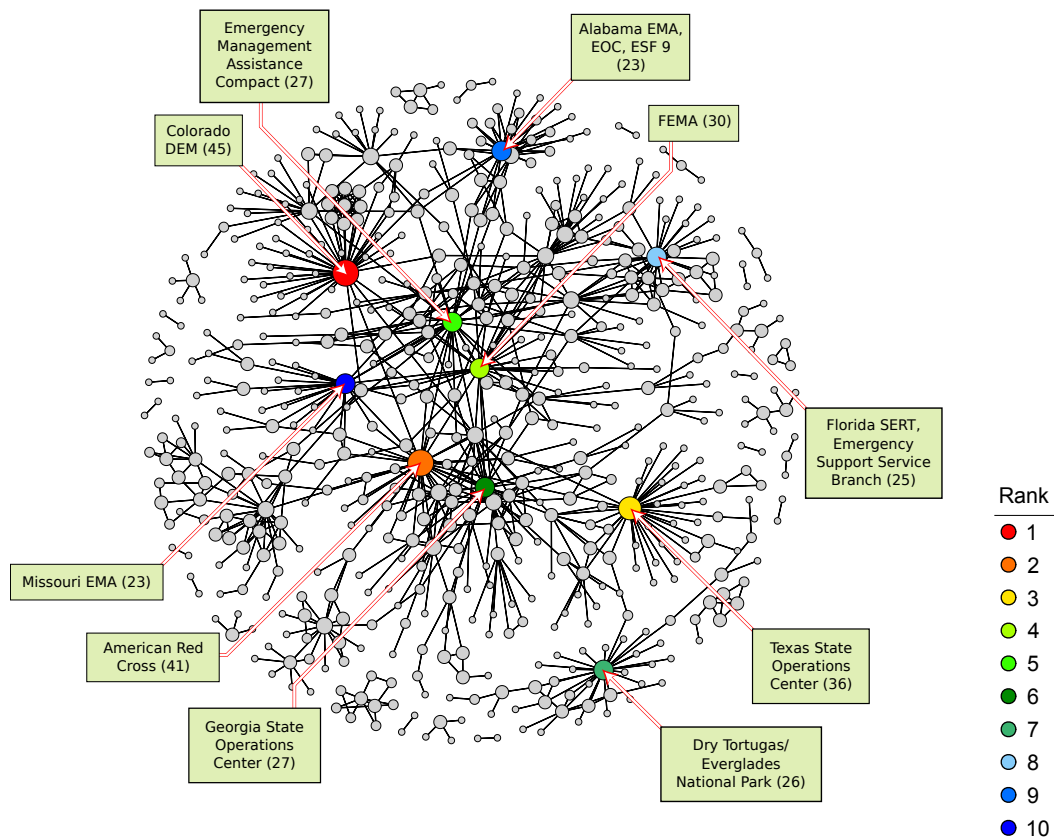


Figure 6: Aggregate Katrina EMON, Vertices Scaled by Degree

Organization Name	Betweenness
American Red Cross	63,200.01
Emergency Management Assistance Compact	37,368.09
U.S. Federal Emergency Management Agency (FEMA)	29,653.28
Texas State Operations Center	25,210.5
Colorado Division of Emergency Management (DEM)	21,045.11
Texas Forest Service	17,823
Dry Tortugas/Everglades National Park	17,581.5
U.S. Forest Service, Atlanta, GA	17,404
Humane Society of the US	15,923.23
Georgia State Operations Center	13,555.81

Table 8: Ten Highest Betweenness Central Organizations

an organization involved in a disaster scenario will be well equipped to maintain many direct ties to other organizations, out of both circumstance and necessity. Such factors may play a role in explaining the prominence of “outside” entities such as the Colorado Division of Emergency Management, which occupies the highest rank on degree in the Katrina network. Despite being far from the path of the storm, the Colorado DEM maintained more direct contacts with other agencies than any other agency mentioned in any of the SITREPs. While many of these contacts were to non-Colorado entities, a major factor in the centrality of the Colorado DEM was its role in coordinating with other units dispatched from the state to the disaster site. For instance, a September 5, 2005 press release by then governor of Colorado Bill Owens notes that among the responders sent to the stricken area was a team from the Colorado DEM experienced in post-hurricane relief. In addition, almost 700 members of Colorado’s National Guard were sent to various damaged areas (Owens, 2005). Although organizationally distinct, these closely related entities (in the sense of the organizational lineage structure) tended to mobilize together, and were especially likely to collaborate with one another. While counter-intuitive, the presence of numerous, highly active outside organizations is in line with previous research on the mass convergence of individuals and organizations during disasters (Fritz and Mathewson, 1957; Mileti et al., 1975; Auf der Heide, 1989; Drabek and McEntire, 2002; Drabek, 2003). We also note the representation of emergency management agencies from Florida and Georgia, which are located in regions for which hurricanes are a recurrent hazard, as significant players in the network. For such organizations, proximity to the storm track, experience in the domain, and institutionalized connections (e.g., mutual aid agreements) may all have played a role in encouraging extensive collaboration in the immediate post-impact period.

While degree is useful for identifying organizations with extensive collaborative activity, betweenness is a better indicator of the extent to which an organization collaborates with partners not otherwise closely linked to one another. In the Katrina EMON, the organizations highest in betweenness are indicated in Table 8. Degree and betweenness are typically correlated, and many of the same organizations that rank highest in degree also rank highly in betweenness centrality. The American Red Cross (ARC) plays the largest bridging role in the Katrina EMON, collaborating with a wide range of organizations from many different communities. Such behavior is consonant with the unique statutory role of the Red Cross under the then-active National Response Plan (DHS, 2004), which mandates that it serve as a primary bridge between voluntary organizations, providers of medical services and relief supplies, federal agencies, and the general public. With a betweenness score nearly twice that of the next-highest scoring organization (and more than twice

Organization Name	Closeness
American Red Cross	0.35
U.S. Federal Emergency Management Agency (FEMA)	0.32
Emergency Management Assistance Compact	0.32
Salvation Army	0.31
Missouri Emergency Management Agency (EMA)	0.3
Colorado Division of Emergency Management (DEM)	0.29
Georgia State Operations Center	0.29
Texas State Operations Center	0.29
Virginia State Emergency Operations Center (SEOC)	0.28
Texas Governor’s Division of Emergency Management (DEM)	0.28

Table 9: Ten Highest Closeness Central Organizations

that of FEMA), we can see that the ARC did indeed occupy a uniquely prominent bridging role during the first days of the unfolding disaster.

As with degree, it is interesting to note that many of these “bridging” organizations were headquartered in areas that allowed them to continue to function without worry of destruction from the hurricane. By being sited away from the center of damage, many of these organizations were able to continue conducting business from their headquarters location and maintain communication with others. As such, this may have increased the chances that they would serve as conduits for information and resource exchange among others in the network.

Finally, closeness centrality has been used to assess the extent to which a given network position is generally proximate to others in a social network. To be the “closest” actor in a social network is to have the shortest paths to all other actors in the network compared to all other actors. A definitional constraint on closeness centrality is that an actor’s distance from (or closeness to) another actor for which there is no path is poorly defined (and generally treated as infinite). That is, the distance between actors in a network that have no paths between them is undefined; this has the net effect of reducing closeness for all actors involved to zero, making the measure effectively useless on disconnected graphs (Wasserman and Faust, 1994). Because the aggregated Katrina EMON is not fully connected, we cannot usefully apply closeness to the graph as a whole. Instead, we limit ourselves to considering the relative closeness of vertices *within* the graph’s giant component. As such, the closeness measure used here was computed for the 497 members of the main component in the network, out of 1,577 total vertices in the graph. The ten organizations with the highest value of closeness within the giant component are listed in Table 9.

Once again, many of the same organizations reappear as central players: the American Red Cross, FEMA, the Emergency Management Assistance Compact, the Colorado DEM, the Georgia State Operations Center, and the Texas State Operations Center. The organizations highest on this measure have the theoretical potential to pass communications and/or resources to other organizations by traversing the smallest number of steps in the network. That is, if we take the aggregate EMON as a rough proxy for the capacity to send information or resources during the study period, these organizations could pass such material to other organizations in the main component with said having to pass through fewer hands (on average) than low-closeness organizations. Although this does not in and of itself guarantee that organizations in these positions *did* engage in this efficient behavior, they are more likely to have had the opportunity to do so than equivalent organizations in low-closeness positions. As such, knowledge of which organizations are likely to have high closeness may allow organizations like those listed here to plan for more effective use of their

structural positions in EMONs arising from future disasters. While the organizations highest in betweenness have the greatest ability to bridge and filter connections among others, those highest in closeness centrality have the potential to disseminate key information to others in the network in the shortest amount of time (and with minimal distortion). Given the vital role of improvisation in disaster response (Wachtendorf, 2004), the capacity for such organizations to serve as low-latency coordinators may be of particular importance.

3.5 Cores and Cohesion

In Section 3.3, we noted a seeming paradox: despite the sparseness and apparently tree-like structure of the Katrina EMON, it in fact contains a surplus of triangles. To understand how this can be so – and to get a sense of what may explain the phenomenon – we close this section with a look at cohesion in the aggregate network.

A useful method of revealing cohesive substructure in a large graph is the examination of its *cores* (Seidman, 1983). A (degree) k -core of graph G is a maximal set of vertices such that all members of the set are adjacent to at least k other members. Although cores are not necessarily cohesive (or even connected), higher-order cores (i.e., those with $k > 1$) are necessarily *unions* of sets that are at least biconnected. Thus, all members of a high-order core belong to robustly connected subgroups, although those subgroups may or may not be connected to each other. Because k -cores can be used to identify sets of cohesive subgroups, and because k -cores are easily computed even for large networks, they are of considerable utility for exploratory analysis of networks such as the aggregate Katrina EMON.

An initial visualization of the Katrina EMON showing core membership is shown in the top left panel of Figure 7. This figure depicts the 1-core, or the network formed by all vertices having at least one tie to some other vertex in the core; eliminated by this selection are the isolates, who belong only to the 0-core. It should be noted that another useful feature of the core structure is its hierarchical decomposibility: since any member of the k th core is necessarily a member of every lower order core, the cores form a nested structure of increasing local cohesion on the underlying graph. Let the k th *shell* of graph G be the set of vertices belonging to G 's k -core, but not to the corresponding $k + 1$ -core. Then the 0-shell consists of the isolates, the 1-shell consists of vertices belonging to trees or pendant trees, the 2-shell consists of vertices belonging to 2-connected sets, etc. Labeling each vertex by its shell membership thus allows us to identify regions of higher local cohesion within the broader network. This is shown in Figure 7 via vertex coloring, with shell numbers indicated by the legend in the lower-right corner of each panel. Examining the 1-core structure (top left), we can immediately see that the numerically dominant 1-shell conceals a smaller (but still substantial) collection of cohesively connected organizations. Cohesion is thus present within the network, but it is clearly localized among a sub-population of organizations.

Focusing only on those vertices belonging to sets that are at least biconnected (the 2-core) leaves us with the structure shown in the top right panel of Figure 7. While much smaller than the EMON as a whole, this portion of the network still contains 241 organizations (approximately 15%). As can be appreciated from Figure 7, the 2-core is itself quite inhomogeneous, consisting of a combination of loosely connected cohesive units, independent cohesive groups, and tree-like structures centered on small numbers of nodes having shared relations to numerous non-adjacent alters. Stripping away those organizations existing only within the 2-shell (Figure 7, bottom left panel) reveals that just under half of the organizations belonging to the 2-core (106, or 44%) are embedded in local groups with an even higher level of cohesion. Like the 2-core, the 3-core is substantially inhomogeneous, being composed of several distinct clusters linked by a complex of organizations with extensive cross-cutting ties. Removing the 3-shell (Figure 7, bottom right panel) eliminates most of these

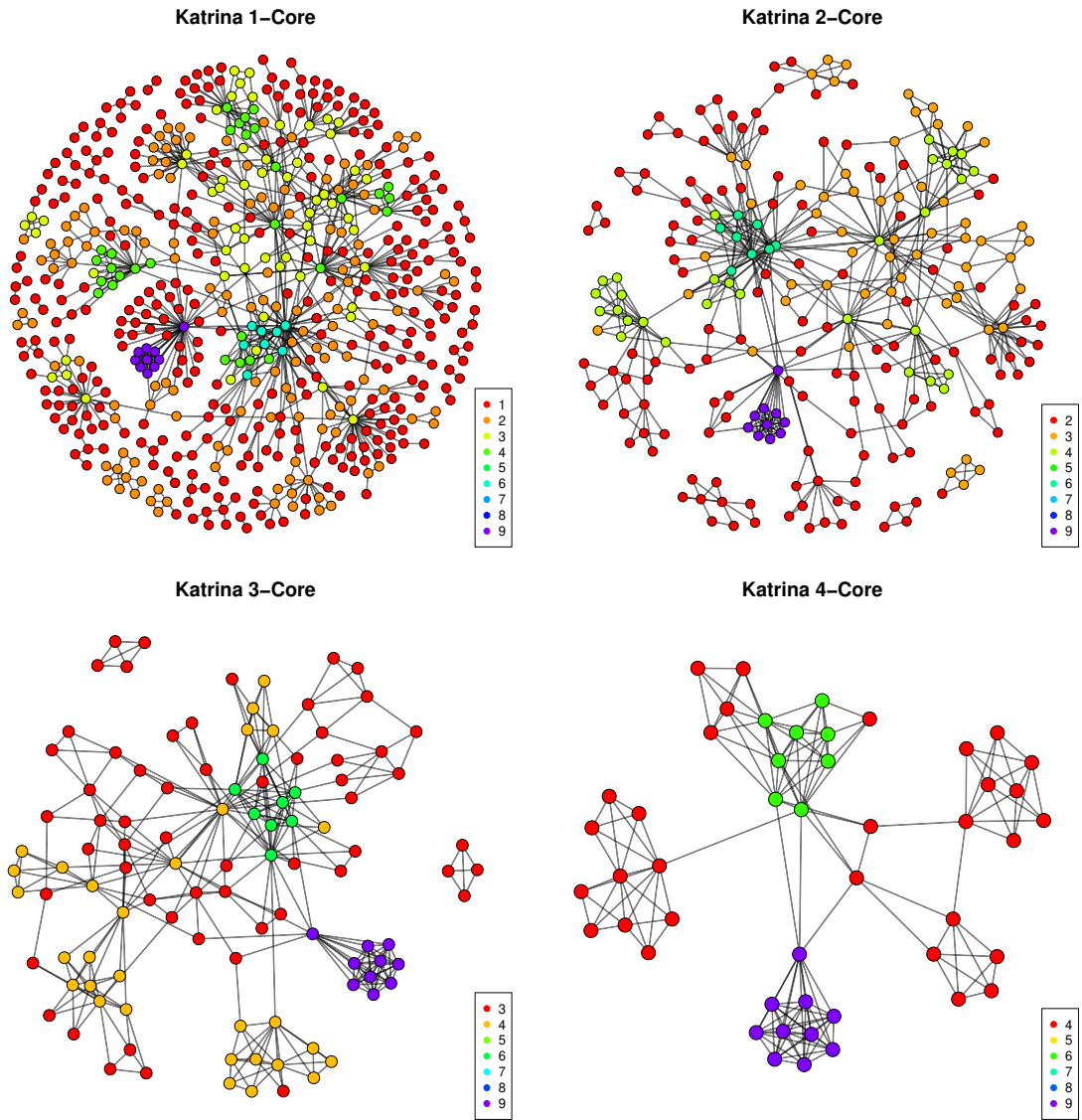


Figure 7: Aggregate Katrina EMON, 1, 2, 3, and 4-Cores; Vertices Colored by k -shell Membership

boundary spanners, revealing a “hard core” of five highly cohesive clusters. It is worth noting, however, that even these clusters are connected to one another by a small number of boundary spanners, and indeed the two most cohesive subgroups within the network are directly tied to one another. The Katrina EMON as a whole, then, can be thought of as a loosely connected set of highly cohesive clusters, surrounded by an extensive “halo” of pendant trees, small independent components, and isolates.

If the inner structure of the Katrina EMON is built around a relatively small set of cohesive subgroups, it is natural to ask whether these groups appear to reflect the action of institutional or task-related factors, versus idiosyncratic (and thus effectively random) effects. While randomness can never be definitively dismissed, examination of the organizations involved strongly suggests the former explanation. Figure 8 depicts the Katrina 3-core, with vertices colored by affiliation and type. As can be seen, the clusters comprising the 3-core are divided almost perfectly along institutional lines, with immediately identifiable clusters corresponding to Alabama, Colorado, Florida, Georgia, and Virginia state and local governmental organizations, U.S. federal organizations, and NGOs involved in humanitarian response. Even within these divisions, we find task-related homogeneity: for instance, the larger portion of the humanitarian cluster is dominated by organizations related to animal welfare, veterinary medicine, and animal rescue/relocation, while its smaller, independent component consists of various volunteer organization (VOAD) collectives. Likewise, much of the federal cluster consists of organizations involved in energy policy and infrastructure (a sector that was heavily mobilized due to the impact of the disaster on nationally significant oil resources), the Alabama cluster is dominated by operations and rescue teams, etc. Thus, where intensive, cohesive collaboration structures developed, they tended to form at the intersection of common institutions and common task domains.

While the higher-order cores of the Katrina EMON are dominated by institutionally homogeneous clusters, it is also noteworthy that these clusters are held together by a congeries of organizations that are often distinct from the clusters they connect. Some of these organizations are highlighted in Figure 8; among them are major national players such as the American Red Cross and FEMA, as well as important regional or case-specific actors such as the Colorado DEM and the Emergency Management Assistance Compact. In some cases, the key boundary spanners are clearly task-related. For instance, the U.S. Department of Agriculture emerges as an important organization connecting the animal welfare subgroup, FEMA, and the Colorado DEM – although not stereotypically thought of as a major player in emergency response, the Department’s unique mix of resources, jurisdiction, and contacts make it a natural bridge between federal, state, and non-governmental organizations working to manage the disruption to livestock and other animal populations resulting from disasters that impact rural areas. In other cases, boundary spanning organizations are clearly institutionalized coordinators (in the sense of Petrescu-Prahova and Butts, 2008) such as FEMA or state emergency management departments, whose formal roles involve coordinating the actions of other organizations during emergencies. Analogously to what has been found in studies at the individual level (Butts et al., 2007; Petrescu-Prahova and Butts, 2008), coordination roles in inner core of the Katrina EMON appear to be filled by a combination of organizations with a standing mandate to bridge diverse groups and organizations whose centrality emerges from task and resource considerations that are peculiar to the specific event. Although the latter may be case specific, it should be noted that they are neither arbitrary nor entirely unpredictable; indeed, a major goal of recent U.S. government planning activities in the wake of disasters such as Katrina has been to identify the types of disruptions that are likely to arise from various kinds of hazards, and to prepare organizations operating in the associated domains for the possibility that they may be thrust into a coordinative role when disaster strikes.

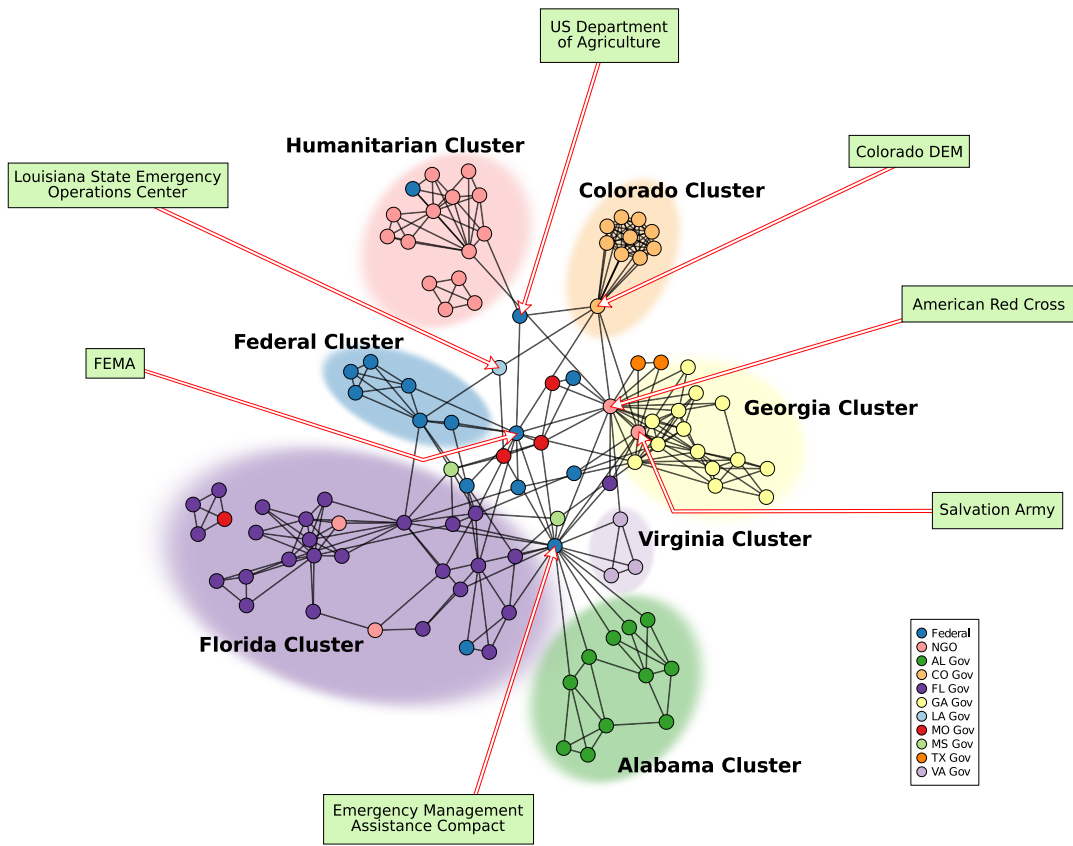


Figure 8: Aggregate Katrina EMON, Detail of 3-Core Structure

4 Discussion

Drawing historical network information from documentary sources raises a number of methodological challenges. Here, we briefly consider some of these issues, both with respect to the present data set and to the practice of data collection in future EMON studies.

4.1 The Role of Source Organizations

Much—if not most—social network data arises from what can be called “own tie” self-report designs of one form or another. While many such designs exist (see Marsden (2005) for a discussion), all have in common the property that sampled entities provide information solely on their own relationships. Families such as the complete ego-net and cognitive social structure (CSS) designs (Krackhardt, 1987), on the other hand, provide the possibility of using sampled entities as *informants* to reveal edges among third parties. (See Butts (2003) for a review.) The approach pursued here lies in some sense between pure own-tie reporting (in which only the informant’s ties are elicited) and a full CSS design (in which every informant is queried regarding every tie). Source organizations are assumed to report their own activities, but generally report on those of other organizations as well—unlike a CSS, however, sources may omit third parties that are judged not salient for their current operations, and/or of which they are unaware. Thus, we would expect to have the greatest information on ties among source organizations, and from source organizations to others in the network; ties among non-source organizations are less certain. With this in mind, it is useful to consider separately the role played by source organizations in the Katrina EMON itself, and to ascertain the extent to which information reported by these organizations provides substantial coverage of events beyond themselves. While we cannot rule out more subtle biases, the results of our simple heuristic checks on the sources clearly show that our data collection design yielded an aggregated network that is not reducible to the contents of each source organization’s ego net.

In addition to reporting on the response effort and on ties between other organizations, the source organizations (many of which were highly placed emergency management agencies) were also important actors in their own right. Because they tended to play especially active roles within the Katrina response, source organizations would be expected to have higher degrees in the Katrina EMON: organizations issuing SITREPs are generally larger than other organizations, with more resources and more institutional responsibility for coordinative activity. However, a strong relationship between high degree and status as a source organization—for instance, if all high degree organizations were source organizations and/or all sources were high degree organizations—could imply that activities of other high-degree organizations were not effectively captured. As a heuristic check on the extent of source organization degree bias, then, we compare the marginals of source organization degrees to those of all organizations in the Katrina EMON.

As expected, source organizations do tend to have higher degrees (source organizations have a mean degree of 7.76 versus 1 for non-sources). However, source organizations do not dominate the upper tail of the degree distribution (of the top 20 organizations, only 5 are sources), and 43% of sources have degree less than or equal to the global mean (i.e., 1 or 0). This suggests that the degree distribution is not simply an artifact of source organizations reporting only on their own activities. On the contrary, the observed distribution is consistent with what would be expected (*prima facie*, at least) given the nature of the organizations involved.

An even more direct test of this notion is provided by considering the extent to which source organizations report on organizations and/or relationships with which they are not involved. On average, source organizations report on approximately 82 other organizations with which they have no collaborative relationship, and approximately 34 third-party edges. Of the latter, an average of

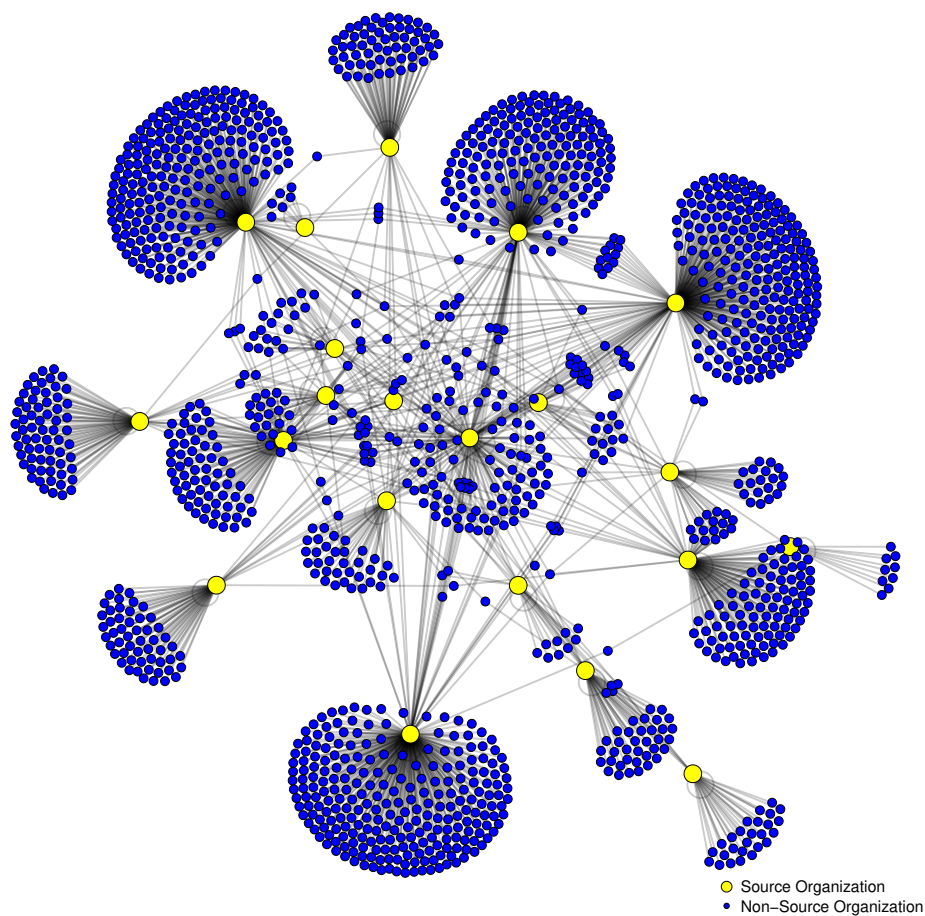


Figure 9: Bipartite Graph of Katrina EMON Source and Non-Source Organizations; Edges Indicate Organizations Reported On, by Source

22 are ties among third parties that are *both* non-adjacent to the source (i.e., that are beyond the source’s second order neighborhood). Sources typically report on a far larger set of organizations than are in their own neighborhoods, and describe many more collaborative relationships than those involving themselves (with many relationships reported among organizations that themselves have no direct connection to the source). While sources may indeed be more aware of activities undertaken by themselves or by their collaborators, the conjecture that source reports are simply a reflection of those activities can clearly be rejected.

Another factor to consider is the overlap in source reports. While it would be expected that certain source organizations would report on particular types of ties (e.g. the Humane Society of the United States reporting on American Veterinary Medical Association VMAT’s tie to itself), we would expect that some organizations should also be reported on by multiple sources. Figure 9 is a bipartite (two-mode) graph of the 21 sources by the 1,577 organizations in the EMON. This graph is constructed from reporting relationships rather than collaboration, such that ties represent source organizations (yellow) reporting on non-source organizations (blue). Loops on yellow vertices indicate that a source organization reported on collaboration between itself and another organization. Many subgraphs within this network have a “mushroom” shape, indicating that many organizations

are mentioned by only one source. On the other hand, we also see many blue nodes with multiple edges, showing that a number of organizations are mentioned in several source accounts.

While this source overlap is limited, it is non-trivial. Among vertices having at least one edge in the EMON, 11.55% are named by more than one source, while 11.33% of isolates in the EMON are named by more than one source. In all, 180 organizations receive multiple reports. Organizations in this latter category do not have significantly more ties than those reported by a single source ($p = 0.8714$), suggesting that EMON degree is not an artifact of visibility. Of the source organizations themselves, five were mentioned by other source organizations: fdem, gagmag, miema, humane, and usnifc. The majority are thus mentioned only once (and, indeed, this frequency does not differ significantly from that for the rest of the organizational population, $p = 0.2092$).

In sum, it is clear that our data lies between the extremes of CSS designs (in which all sources report on all ties) and own-tie designs (in which sources report only on their own interactions). Each source reports on a wide range of activities beyond its own ego net, and the resulting aggregate is not simply a reflection of the source organizations' activities. On the other hand, most organizations are uniquely reported, a feature that seems to be unrelated to the collaborative activity of the organization in question.

4.2 SITREPs Versus Media Accounts

It is worth comparing the type of source utilized here with the other major archival source employed in disaster EMON research, namely media (particularly newspaper) coverage. Media sources act as “information integrators” during disasters, providing accounts that synthesize inputs from a number of informants (Auf der Heide, 1989). These accounts are frequently updated during major events, and are readily available to researchers; such features make them very attractive as materials from which to extract EMON data. By comparison, SITREPs are relatively difficult to obtain, and may or may not be updated with similar frequency (depending on the issuing organization). On the other hand, SITREPs also hold certain advantages over media accounts. As documents prepared for internal use by the responders themselves, SITREPs are *prima facie* more consistent with the state of organizational knowledge than statements issued to the press (which may be abbreviated or manipulated for reasons of liability, intelligibility to a non-technical audience, or adherence to a preferred frame (Tierney et al., 2006)). Similarly, SITREPs are typically focused on events that are directly related to task performance, whether or not these events are believed to be of interest to the public at large; by contrast, media organizations are strongly motivated to concentrate coverage on events with immediate public impact. As such, information provided in SITREPs may provide a better basis for reconstruction of task performance, especially where such performance does not directly involve lifesaving or other easily explicable components. This distinction is further exaggerated by the fact that SITREP authors are usually working in the field (or are in direct contact with those working in the field), a circumstance that may or may not be true of those who write media accounts. While some reporters will be deployed to the impact site, others will be reliant on second- or third-hand information (possibly from the responding organizations themselves). Since the primary audience for these accounts is also removed from the response process itself, incentives to convey accurate and detailed information regarding specific organizational actions (or the spatial and relational context of those actions) may be weak. As SITREP readership is heavily concentrated among those who are both present and actively working in the field, incentives for accuracy are substantially increased.

While media accounts have many weaknesses as sources for EMON research, we do not wish to suggest that they are without merit. Media organizations with an extensive contact network may be very effective at collecting information on local conditions, especially where public demands for

detailed information are strong. The differing audiences for which media organizations produce accounts may lead them to avoid “blind spots” to which SITREP authors may be prone (e.g., the activities of small, private sector organizations). Since media organizations are specifically designed for information gathering, transmission, and dissemination, they may be able to effectively maintain situational awareness even under adverse conditions. Indeed, emergency management organizations themselves often turn to media sources for information on current conditions outside their immediate zone of operations (Auf der Heide, 1989), suggesting that the flow of information is more bidirectional than might be anticipated. Despite our reservations about the quality of media reports, therefore, we do not recommend that they be abandoned as a source in EMON research. Rather, we suggest that they be employed where available, ideally using a framework that integrates the different properties of these sources. The informant accuracy paradigm used by Butts et al. (2007) to combine personal accounts of responder interactions in the World Trade Center disaster may constitute a possible approach to this problem.

4.3 Implications for Automated Information Extraction

Given the substantial human investment required in extracting network information from documentary accounts (as described in Section 2), the potential gains from the use of automated information extraction in cases like that studied here are profound. As documents such as SITREPs are relatively stylized in form, and since many of the locations and organizations mentioned within them belong to a known population, the present case might seem to be a good target for the use of automated text analysis. While we see great long-range potential in such efforts, our experiences have highlighted a number of challenges to automated coding of organizational network information from SITREPs or similar documents. We mention a few of these here, as a resource for researchers who may be interested in pursuing this approach.

One consideration that should be borne in mind when working with SITREPs (and other field documents) is that they are texts produced by human writers for use by human readers occupying the same context, within a narrow time window. Time pressure and human failings naturally lead to minor errors and variability; since the intended readers are expected to intelligently use shared context and background information when interpreting the account, there is little incentive for writers to purge these features from their texts. As a result, SITREPs often contain spelling errors, typos, and other forms of human error. For example, “St. Paul’s Episcopal Church” was rendered in one document as “St. Pauls Apiscaple Church.” This required correction by a human coder, who had to 1) note the likely misspelling, and 2) verify through other means that there was no “Apiscaple Church” in the area. Organization and place name consistency was another problem that required a human coder to use context to determine the appropriate representation of entities within the EMON. For instance, the U.S. Federal Government might be referred to as the “U.S. Government” or “Federal Government,” and New Orleans, LA might be referred to as “The City of New Orleans,” “New Orleans,” or “NOLA.” Such nomenclature is often transparent to a human coder, but is not trivial for purposes of automated recognition (requiring, for instance, the labor-intensive creation of a specialized thesaurus for use with the corpus). More difficult yet are cases involving the use of pronouns or other indirect references to organizations in the text (or contextual references to the issuing organization, as in “*our units* are being dispatched”). While clear to a human reader, these references can be very difficult for automated systems to identify and disambiguate.

Finally, we note that fairly minor differences in document formatting and layout may pose problems for some text analysis systems. For instance, some documents in our corpus are written entirely in capital letters, making it impossible to use heuristics based on capitalization (e.g., for recognition of proper nouns). The use of headings and bullet lists also appears innocent at first

blush, but may pose problems for tools that assume prose text with standardized sentence structure (e.g., for part-of-speech recognition). On an even more prosaic note, “noise” characters created by conversion of documents from one form to another (or present in the original documents for similar reasons) may interfere with analysis routines as well. Documents can, of course, be cleaned and standardized to remove these obstacles, but this is in and of itself a labor intensive process.

Given these factors, our assessment is that fully automated extraction of detailed network information from reports such as those used here will prove extremely challenging. Tools for this purpose must be able to handle inconsistencies in text style and layout; minor errors in spelling, punctuation, and grammar; use of colloquial and/or stylized entity references; use of pronouns and other forms of indirect reference; and a certain amount of textual “noise.” Given the tremendous volume of documentary evidence available on disasters and other, similar events, automated methods for document coding could prove revolutionary if practical. If our experience is any guide, however, the way will be difficult.

5 Conclusion

This paper has demonstrated the use of archival research methods to reconstruct the dynamic network of interorganizational collaboration that emerged after a major disaster. As such, it adds to the small but growing set of disasters for which EMON data is available. Given the growing vulnerability of human populations to natural hazards worldwide (de Sherbinin et al., 2007), an understanding of the manner in which organizations mobilize and coordinate their response activities is of vital practical importance. Likewise, the study of cases such as Hurricane Katrina provides us with an important scientific window into the formation of structure within a disrupted social system—in some respects, a macro-social version of Harold Garfinkel’s famous breaching experiments (Garfinkel, 1967). By measuring and analyzing collaboration in the aftermath of the Hurricane Katrina disaster, we hope to advance knowledge on both fronts.

6 References

- Auf der Heide, E. (1989). *Disaster Response: Principles of Preparation and Coordination*. Mosby, St. Louis, MO.
- Banipal, K. (2006). Strategic approaches to disaster management: Lessons learned from Hurricane Katrina. *Disaster Prevention and Management*, 15(3):484–494.
- Barabási, A.-L. and Albert, R. (1999). Emergence of scaling in random networks. *Science*, 206:509–512.
- Bollobás, B. (2001). *Random Graphs*. Cambridge University Press, Cambridge, second edition.
- Bourque, L. B., Siegel, J. M., Kano, M., and Wood, M. M. (2006). Weathering the storm: The impact of hurricanes on physical and mental health. *Annals of the American Academy of Political and Social Science*, 604:129–151.
- Butts, C. T. (2003). Network inference, error, and informant (in)accuracy: a Bayesian approach. *Social Networks*, 25(2):103–140.
- Butts, C. T. and Cross, B. R. (2009). Change and external events in computer-mediated citation networks: English language weblogs and the 2004 U.S. electoral cycle. *Journal of Social Structure*, 10.

- Butts, C. T., Petrescu-Prahova, M., and Cross, B. R. (2007). Responder communication networks in the World Trade Center Disaster: Implications for modeling of communication within emergency settings. *Journal of Mathematical Sociology*, 31(2):121–147.
- Comfort, L. K. and Haas, T. W. (2006). Communication, coherence, and collective action: The impact of Hurricane Katrina on communications infrastructure. *Public Works Management and Policy*, 10(4):328–343.
- Comfort, L. K. and Kapucu, N. (2006). Interorganizational coordination in extreme events: The World Trade Center attack, September 11, 2001. *Natural Hazards: Journal of the International Society for the Prevention and Mitigation of Natural Hazards*, 39(2):309–327.
- de Sherbinin, A., Chen, R. S., and Levy, M. A. (2007). What does climate change mean for the hazards community? *Natural Hazards Observer*, 31(6):11–13.
- DHS (2004). *National Response Plan*. Department of Homeland Security, Washington, DC.
- Drabek, T. E. (2003). Strategies for coordinating disaster responses. Technical Report 61, Institute of Behavioral Sciences, University of Colorado, Boulder, CO.
- Drabek, T. E. and McEntire, D. A. (2002). Emergent phenomena and multiorganizational coordination in disasters: Lessons from the research literature. *International Journal of Mass Emergencies and Disasters*, 20(2):197–224.
- Drabek, T. E., Tamminga, H. L., Kilijanek, T. S., and Adams, C. R. (1981). *Managing Multiorganizational Emergency Responses: Emergent Search and Rescue Networks in Natural Disaster and Remote Area Settings*. Number Monograph 33 in Program on Technology, Environment, and Man. Institute of Behavioral Sciences, University of Colorado, Boulder, CO.
- Dynes, R. R. (1970). *Organized Behavior in Disaster*. Heath Lexington, Lexington, MA.
- Freeman, L. C. (1979). Centrality in social networks: Conceptual clarification. *Social Networks*, 1(3):223–258.
- Fritz, C. E. and Mathewson, J. H. (1957). *Convergence Behavior in Disasters: A Problem in Social Control*. National Academy of Sciences, Committee on Disaster Studies, Disaster Research Group, Washington, DC.
- Gabe, T., Falk, G., McCarty, M., and Mason, V. (2006). *Hurricane Katrina: Social Demographic Characteristics of Impacted Areas*. Congressional Research Service, Washington DC.
- Garfinkel, H. (1967). *Studies in Ethnomethodology*. Prentice-Hall, Englewood Cliffs, NJ.
- Goffman, E. (1959). *The Presentation of Self in Everyday Life*. Social Sciences Research Centre, Monograph no. 2. University of Edinburgh, Edinburgh.
- Gould, R. and Fernandez, R. (1989). Structures of mediation: A formal approach to brokerage in transaction networks. *Sociological Methodology*, 19:89–126.
- Handcock, M. S., Hunter, D. R., Butts, C. T., Goodreau, S. M., and Morris, M. (2003). statnet: A suite of R packages for the statistical modeling of social networks.

- Independent Panel Reviewing the Impact of Hurricane Katrina on Communications Networks (2006). *Independent Panel Reviewing the Impact of Hurricane Katrina on Communications Networks: Report and Recommendations to the Federal Communications Commission*. Wiley Rein and Fielding, Washington, DC.
- Irwin, J. O. (1963). The place of mathematics in medical and biological statistics. *Journal of the Royal Statistical Society, Series A*, 126(1):1–45.
- Johnson, N. L., Kotz, S., and Kemp, A. W. (1992). *Univariate Discrete Distributions*. John Wiley and Sons, New York.
- Jones, J. H. and Handcock, M. S. (2003). An assessment of preferential attachment as a mechanism for human sexual network formation. *Proceedings of the Royal Society, Series B*, 270:1123–1128.
- Kapucu, N. (2006). Interagency communication networks during emergencies: Boundary spanners in multiagency coordination. *American Review of Public Administration*, 36(2):207–225.
- Knabb, R. D., Rhome, J. R., and Brown, D. P. (2005). Tropical cyclone report: Hurricane Katrina, 23–30 August 2005. Technical report, National Hurricane Center, Miami, FL.
- Kobayashi, M. and Takeda, K. (2000). Information retrieval on the web. *ACM Computing Surveys*, 32(2):144–173.
- Krackhardt, D. (1987). Cognitive social structures. *Social Networks*, 9(2):109–134.
- Krackhardt, D. (1994). Graph theoretical dimensions of informal organizations. In Carley, K. M. and Prietula, M. J., editors, *Computational Organizational Theory*, pages 88–111. Lawrence Erlbaum Associates, Hillsdale, NJ.
- Lind, B. E., Tirado, M., Butts, C. T., and Petrescu-Prahova, M. (2008). Brokerage roles in disaster response: Organizational mediation in the wake of Hurricane Katrina. *International Journal of Emergency Management*, 5:75–99.
- Marsden, P. V. (2005). Recent developments in network measurement. In Carrington, P. J., Scott, J., and Wasserman, S., editors, *Models and Methods in Social Network Analysis*, chapter 2, pages 8–30. Cambridge University Press, Cambridge.
- Mayhew, B. H. (1984). Baseline models of sociological phenomena. *Journal of Mathematical Sociology*, 9:259–281.
- Mileti, D. S., Drabek, T. E., and Haas, J. E. (1975). *Human Systems in Extreme Environments*. Institute of Behavioral Science, University of Colorado, Boulder, CO.
- NOAA (2006). Historical north atlantic and east-central north pacific tropical cyclone tracks, 1851–2005.
- Owens, B. (2005). Colorado National Guard deploys personnel to Gulf Coast relief effort.
- Petrescu-Prahova, M. and Butts, C. T. (2008). Emergent coordinators in the World Trade Center Disaster. *International Journal of Mass Emergencies and Disasters*, 28(3):133–168.
- Powell, W. W. (1990). Neither market nor hierarchy: Network forms of organization. In *Research in Organizational Behavior*, volume 12, pages 295–336. JAI Press.

- Powell, W. W., Koput, K. W., and Smith-Doerr, L. (1996). Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*, 41(1):116–145.
- Price, D. J. d. S. (1976). A general theory of bibliometric and other cumulative advantage processes. *Journal of the American Society for Information Science*, 27:292–306.
- Seidman, S. B. (1983). Network structure and minimum degree. *Social Networks*, 5:269–287.
- Simon, H. A. (1955). On a class of skew distribution functions. *Biometrika*, 42:425–440.
- Tierney, K. J. (2003). Conceptualizing and measuring organizational and community resilience: Lessons learned from the emergency response following the September 11, 2001 attack on the World Trade Center.
- Tierney, K. J., Bevc, C., and Kuligowski, E. (2006). Metaphors matter: Disaster myths, media frames, and their consequences in Hurricane Katrina. *Annals of the American Academy of Political and Social Science*, 604:57–81.
- Tierney, K. J. and Trainor, J. (2004). Networks and resilience in the World Trade Center Disaster. In *Research Progress and Accomplishments, 2003–2004*. Multidisciplinary Center for Earthquake Engineering Research, Buffalo, NY.
- Topper, C. M. and Carley, K. M. (1999). A structural perspective on the emergence of network organizations. *Journal of Mathematical Sociology*, 24(1):67–96.
- van Merode, F., Nieboer, A., Maarse, H., and Lieverdink, H. (2004). Analyzing the dynamics in multilateral negotiations. *Social Networks*, 26:141–154.
- Wachtendorf, T. (2004). *Improvising 9/11: Organizational Improvisation Following the World Trade Center Disaster*. PhD thesis, University of Delaware.
- Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications*. Cambridge University Press, Cambridge.
- Williamson, O. (1975). *Markets and Hierarchies, Analysis and Antitrust Implications: A Study in the Economics of Internal Organizations*. Free Press, New York.

Appendix A: Source Organizations

Table 10 maps the abbreviated names of all 21 source organizations to their respective full names for the data analyzed within this paper.

Appendix B: Katrina EMON Data Set

The data set described in this paper has been included with this publication as a library for the R statistical computing system. This library contains the source data and codebook, as well as additional documentation regarding the data coding and preparation process. In the event that the library data file cannot be retrieved from the journal web page, it may also be obtained by request from the corresponding author.

[Data Set for UNIX/Mac](#)

[Data Set for Windows](#)

Abbreviation	Organization Name
alema	Alabama Emergency Management Agency (EMA)
avma	American Veterinary Medical Association
codem	Colorado Division of Emergency Management (DEM)
fldem	Florida Division of Emergency Management (DEM)
flpalmbc	Palm Beach County, FL Department of Public Safety, Division of Emergency Management (DEM)
gagnag	Georgia Mutual Aid Group
gaohs	Georgia Emergency Management Agency (EMA)
humane	Humane Society of the US
iafc	International Association of Fire Chiefs
mnhsem	Minnesota Department of Public Safety Division of Homeland Security and Emergency Management
moesma	Missouri Emergency Management Agency (EMA)
msforres	Mississippi Forestry Commission
tnwillia	Williamson County, TN Emergency Management Agency (EMA)
txdem	Texas Governor's Division of Emergency Management (DEM)
txftbend	Fort Bend County, TX Office of Emergency Management (OEM)
txgalves	Galveston County, TX Office of Emergency Management (OEM)
usea	U.S. Department of Energy, Office of Electricity, Delivery and Energy Reliability
usihs	U.S. Indian Health Service
usnifc	National Interagency Fire Center
usnps	U.S. National Park Service
vadem	Virginia Department of Emergency Management

Table 10: Source Organizations: Abbreviated and Full Names