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Visualizing the Process of Disaster Mental Health Services in the Joso Flood by Network Analyses of Emails

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Joso City, Ibaraki Prefecture, Japan was severely affected by flooding of the River Kinugawa in September 2015. Local psychiatric organizations immediately began providing disaster mental health services (DMHS). In post-disaster settings, DMHS involving organizational interventions by multiple regional institutions are required to support disaster victims. However, little is known about the process of coordinating multiple institutions or determining whether appropriate support has been provided. To elucidate the characteristics of communications that enable effective disaster medical team formation, we conducted network analyses of sender-recipient pairs of emails during the period of DMHS activity. The network analysis is a research method that represents various objects as a network of nodes and edges and explores their structural characteristics. We obtained 2,450 time-series emails from five core members of DMHS, including 32,865 pairs of senders and recipients. The network generated by the emails was scale-free, and its structure changed according to the phases of disaster recovery. In the ultra-acute phase, which lasted about 1 week, spreading information and recruiting people to provide disaster support was given the highest priority. In the acute phase, which lasted about 1 month, support and swift decision-making were essential for directing large numbers of staff. In the mid- to long-term phase, support for staff to share information and experience in small groups was observed. Network analyses have revealed that disaster medical teams must change their communication styles during the mission to adapt to different health needs corresponding to each post-disaster phase.

Keywords: assortativity; disaster mental health services (DMHS); email network; flood; network analysis
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Introduction

Floods are a common type of natural disaster in most countries. In 2017, there were approximately 10,000 human fatalities caused by natural disasters, and floods accounted for more than 60% of these deaths (Benfield 2018). Almost half of the 10 most severe flooding events occurred on the Asian continent.

On September 7, 2015, Typhoon Etau caused record amounts of rain to fall in the Kanto and Tohoku regions of Japan. From September 9-10, the Kanto region had 551 mm of rainfall within 24 hours, and the River Kinugawa burst its banks, flooding the city of Joso in Ibaraki Prefecture. The flood destroyed more than 5,000 houses. Over 6,000 people were evacuated and taken to 39 shelters. The flood waters spread across approximately 40 km^2, covering approximately one-third of Joso. Police and fire services used helicopters and boats to rescue 4,200 residents trapped on rooftops and other locations. Despite extensive drainage work, it took approximately 10 days for the floodwater to dissipate (Geographical Survey Institute of Japan 2015; Lebowitz et al. 2019).

There have been several reports investigating the impact of floods on mental health. Dai et al. (2017)

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reported that the prevalence rates of posttraumatic stress disorder (PTSD) and anxiety were 9.5% and 9.2% among survivors in areas that were severely affected by flooding. Fontalba-Navas et al. (2017) reported that people affected by floods were approximately eight times more likely to suffer the symptoms of PTSD. After the 2011 flood in Thailand, flood victims were approximately 1.5 times more likely to exhibit serious mental illness compared with those unaffected by the flood (Yoda et al. 2017). PTSD is the psychiatric disorder most often associated with disaster trauma exposure (North and Pfefferbaum 2013). PTSD has been reported to occur in up to one-third of survivors, typically following acute stress (North and Pfefferbaum 2013). Major depression has been reported to occur in up to one-quarter of people experiencing stressful life events. Thus, the importance of integrating mental health support into the emergency and medical aspects of disaster responses is widely recognized (Pfefferbaum et al. 2012).

The mental health support required in post-disaster settings includes case identification, triage, and mental health interventions, commonly referred to as disaster mental health services (DMHS) (North and Pfefferbaum 2013). Organizational interventions conducted by multiple regional institutions are necessary to provide these activities. Many countries use disaster medical teams (DMT) (Arziman 2015), with wide-ranging activities. The Major Incident Medical Management and Support program is a training program designed for doctors, nurses and ambulance personnel and contains seven key principles (Advanced Life Support Group 2011). The acronym CSCATTT is used to describe Command and Control, Safety, Communication, Assessment, Triage, Treatment, and Transport. The activities under the first four activities (CSCA) cover medical management at the disaster site, and the last three (TTT) cover medical support. The command and control system should be regulated carefully because close cooperation is needed among different institutions, including police, ambulance services, and medical services (Fuse and Yokota 2010).

Japanese Disaster Medical Assistance Teams (J-DMAT) were established in 2005 to provide on-site disaster responses. The activities of J-DMAT include medical data collection and communication in devastated areas, as well as triage, treatment and transport, providing medical support to hospitals, supporting care units, in-flight treatment of victims who are being evacuated, and supervision of emergency medical technicians (Fuse and Yokota 2010). After the Great East Japan Earthquake, it was clear that mental health support is also needed during the emergency phase of disasters. In 2013, the Japanese Government therefore started to set up Disaster Psychiatric Assistance Teams (DPAT) in each prefecture, as a mental health version of J-DMAT.

At the time of the Joso flood disaster, there was no public DPAT in Ibaraki Prefecture and therefore no specialized DMHS. However, the Department of Psychiatry, University of Tsukuba, and other psychiatric hospitals in Ibaraki Prefecture started to provide psychiatric assistance as soon as the flooding occurred. These hospitals managed providers largely by email, arranging for four patients to be hospitalized, and providing consultations for approximately 140 cases at evacuation sites. This action received a letter of appreciation from Joso City and was considered to be a successful case of disaster assistance. This response has since been used a model of successful CSCA for DPAT training.

However, little is known about the methods that were used to involve multiple institutions in a systematic way, or how appropriate support could be provided so promptly. Few studies have examined communication networks in disaster medical assistance teams in the post-disaster acute phase. We therefore investigated the email relationships among emergency workers providing psychiatric interventions following the Joso flood disaster using network analysis. The aim of the current study was to elucidate the features of email communications among members of the DMHS that enabled coordination and the provision of appropriate support.

Materials and Methods

Data collection

We asked five core members of the disaster psychiatric assistance team for the Joso flood to provide all emails exchanged between 10 September 2015 to 16 December 2015 that were related to disaster support activities. These five people included one professor and two associate professors in the Department of Psychiatry, and one associate professor in the Department of Disaster Psychiatry at the University of Tsukuba hospital, plus the vice-president of Ibaraki prefectural psychiatric hospital. These members were selected because they first proposed the support activities together and organized the DMHS headquarters.

We obtained 2,450 emails from the five individuals. Some emails had multiple recipients (e.g., carbon copy [CC] and mailing list [ML]), so we separated them into pairs consisting of a source and a target. We eliminated duplicate email addresses because some of the people involved had multiple email addresses. In total, the emails contained 32,865 pairs of email senders and recipients, and all pairs were mapped as a directed graph. The activities of DMHS at each point in time are shown in Table 1.

Network analysis

Structures in which some elements are linked to others can be considered networks. When a network is presented graphically, network nodes are connected by edges (Bollobás 1998). When we consider the exchange of emails among people as a network, an email exchanged between two persons constitutes an edge, and each person constitutes a node.

Network analysis has been developed to clarify complex correlations among multiple factors (Bollobás 1998;

Table 1. Timetable for psychiatric assistant activities following the Joso flood disaster.

Date	Event and activities
2015/9/10	Occurrence of the flood
2015/9/12	a: City and prefectural administration sent a request for a mental health team
2015/9/13	b: Mental health team started work at evacuation centers
2015/9/30	c: A joint headquarters for the mental health team and the Japanese Red Cross was set up
2015/10/10	d: The Ibaraki Medical Center for Dementia started visits to older people
2015/10/13	e: Mental health team stopped work at evacuation centers
2015/10/21	f: Counseling team started work
2015/10/25	g: Ibaraki Medical Center for Dementia concluded visits to older people
2015/10/25	h: Health survey for Joso citizens
2015/11/1	i: Visits to people identified as high risk in the health survey started
2015/11/27	j: Counseling team stopped work
2015/12/1	k: Stress-checkup for city employees

a-k refer to timing of events represented in Figures.

Scott and Carrington 2011; Hasan et al. 2012; Kinnison et al. 2012; Liu et al. 2012; Oldham et al. 2012; Shiratori et al. 2014). Emails were examined to facilitate the emergence of structure within the organization from a social network perspective (Tashiro et al. 2010; Wuchty and Uzzi 2011; Kolli and Narayanaswamy 2013; Matthews et al. 2013; Buchler et al. 2016). We also introduced time series variation into email network analysis.

Making static and time series networks

We considered email communications from two points of view: as a whole network and as a time series network. From the perspective of the whole network, we considered the network of all emails sent and received over the 97 days to constitute one network. Analyzing the network as a whole, we determined what type of network structure was formed throughout the entire period. From the point of the time series networks, we separated the emails into shorter periods, and considered them as a set of small networks. Analyzing the time series networks, we were able to determine how the network was created. We considered the whole former network as a "static network", and the latter time series network as a "dynamic network".

We created time series networks from the 32,865 pairs of emails by setting a sliding window with a period of 7 days, and moved the window every 12 hours. Every two consecutive windows overlapped at 6.5 days. We extracted emails included in each window period and created a network from them. We repeated this process to move the window period 180 times, giving 180 networks smoothly serialized over 97 days. The start time of the first window was 2015/9/10 13:37, which was the time at which the first email was sent.

After creating a static and dynamic network, we analyzed each network by calculating several network measures, as described in the following section. All network measures were calculated using R program version 3.4.0 and igraph version 1.1.2.

Network analysis measures

Total-degree distribution: The degree refers to the number of edges belonging to a node. A node has two types of degree: in-degree and out-degree. In-degree is defined as the number of edges that reach to a particular node, and out-degree is defined as the number of edges that leave from a particular node. Total-degree is the sum of in-degree and out-degree. The total-degree distribution presented a distribution of the degree of each node. The total-degree distributions of real-world networks are typically skewed and non-normal (i.e., non-Gaussian), with heavy tails (Barabási et al. 1999; Strogatz 2001; Buchler et al. 2016). These networks include, for example, the sizes of cities, earthquakes, solar flares and personal wealth (Newman 2004). If the appearance of the degree distribution of a network was heavy-tailed, the network was presumed to be typical and common in real-world situations, and was denoted as a scale-free network. Pareto's law of the vital few (20%) and the trivial many (80%) is considered an aspect of the scale-free network.

Cluster analysis: The network grew to a certain size, and sub-networks were formed within it. Cluster analysis can reveal the cohesive sub-groups into which a network can be divided. There are a range of cluster analysis methods. We used the spin glass method, which is the most accurate method for detecting clusters (Fortunato 2009).

Network level measures: We calculated five network level measures: number of nodes, edge density, transitivity, reciprocity, and assortativity coefficients. These network level measures were applied for static network and time series networks.

Number of nodes. The number of nodes is the number of participants who sent and/or received emails in the network. For the static network, the number of nodes does not change. For a dynamic network, the number of nodes varies with each window period.

Edge density. The edge density of a graph refers to the ratio of the number of edges and the number of possible edges. More complicated networks have a higher density. When we calculated the edge density, we removed multiple edges and loop edges from each graph.

Transitivity. Transitivity measures the probability that the adjacent nodes are connected. This is also called the clustering coefficient. Transitivity reveals the presence of triads (connections between three nodes). When three nodes connect to each other, even if one edge disappears, indirect connections of these three nodes are maintained. In this sense, transitivity represents the robustness and stability of the network.

Reciprocity. The measure of reciprocity defines the proportion of mutual connections in a directed graph. In this email network, reciprocity referred to the proportion of the edges between two nodes who sent and received emails between each other. Reciprocity is most commonly defined as the probability that the opposite counterpart of a directed edge is also included in the graph. High reciprocity of a network represents a high probability of bidirectional exchange of information, not unilateral command.

Assortativity coefficients. The assortativity coefficient measures the level of homophily of the graph, based on the node degree. Many networks show "assortative mixing" in their degrees, for example, a preference for high-degree vertices to attach to other high-degree vertices. Others show disassortative mixing, whereby high-degree vertices attach to low degree vertices. If the assortativity coefficient is positive, this indicates assortative mixing (Newman 2002).

Ethical issues

Before obtaining the emails, informed consent was obtained from all participants including the five core members. This study was conducted with permission from the medical ethics committee of the University of Tsukuba (Permission No.1027).

Results

Static network analysis

There were 183 participants in the network, from a wide variety of occupations and institutions. There were 70 doctors, 44 clerical staff, 16 social workers, 15 nurses, 15 psychologists, six journalists, six public health nurses, five research scientists, three volunteers, two students, and one occupational therapist. There were 86 participants from universities in Ibaraki, 32 from private hospitals in the prefecture, 22 from the Ibaraki regional government, 8 from the Red Cross, 6 from professional organizations, 5 from the secretariat of the national DPAT, 5 from nonprofit organizations or non-governmental organizations, 5 from the press, 5 from universities outside Ibaraki Prefecture, 4 from regional governments other than Ibaraki, 3 from Joso government, and 2 from national institutions.

Cluster analysis indicated that the participants in the network could be split into four groups. Table 2 shows the number of people from each type of affiliated institution in each group. Cluster 1 had 33 members, 24 of whom were from private hospitals in Ibaraki Prefecture and the Ibaraki Medical Center for Dementia. We therefore named cluster 1 the "regional assistance group." Cluster 2 had 74 members, 46 of whom were from universities in Ibaraki. Three of the five core members, a professor of the department of psychiatry (PP), an associate professor of psychiatry (APP) and an associate professor of disaster psychiatry (APDP), were in this cluster. All of the members affiliated with universities and regional governments outside Ibaraki were also in cluster 2. Cluster 2 was therefore named the "leading group." Cluster 3 had 42 members, of whom 28 were employed by universities in Ibaraki Prefecture, and 12 were employed by the Ibaraki regional government. This cluster contained the biggest group from Ibaraki regional government. We therefore named cluster 3 the "public service group." Cluster 4 had 34 members, from a wide range of institutions. We therefore named this group the "variety group."

The total-degree represented the amount of email communication by each individual node. In a whole static network, the distribution of degree was asymmetrical. As shown in Fig. 1, degree rank is plotted on the x-axis, with 1 being the individual with the highest degree. The percentage of total-degree in the whole network belonging to each individual is plotted on the y-axis. Here, a few key nodes dominated the email traffic in that network, and most members had very few emails. In the degree distribution, an inserted line indicated that 12% of the nodes were responsible for 80% of the edges.

In Fig. 2, the total-degree of each node was plotted on the x-axis and the rank order of total-degree was plotted on the y-axis, to give a steeper curve. The curve was fitted to a power curve ($y = 421.35x^{-0.472}$, $R^2 = 0.824$), to give the network scale-free properties. Heavy-tailed distributions are common in scale-free complex networks, and are seen in many natural and artificial systems, including protein interaction networks, neural networks, ecological niches in the food web, the world wide web, the global economic system, and social networks (Xiao Fan and Guanrong 2003; Clauset et al. 2008).

The number of nodes was 183. The edge density of the static network was 0.064, the transitivity was 0.552, the reciprocity was 0.285, and the assortativity coefficient was 0.020.

Table 2. Affiliated institutions and cluster membership.

Affiliated institutions	Cluster membership				Total
	Cluster 1	Cluster 2	Cluster 3	Cluster 4	
Universities in the prefecture	4	46	28	8	86
Private hospitals in the prefecture	24	5	1	2	32
Ibaraki regional government	1	6	12	3	22
The Red Cross	2	2		4	8
Professional organizations	1	3	1	1	6
DPAT		3		2	5
NPO or NGO				5	5
Press				5	5
Universities other than Ibaraki Prefecture		4		1	5
Regional government other than Ibaraki		3		1	4
Joso city government	1			2	3
National institutions		2			2
Total	33	74	42	34	183

The participants in the network were split into four groups by cluster analysis.

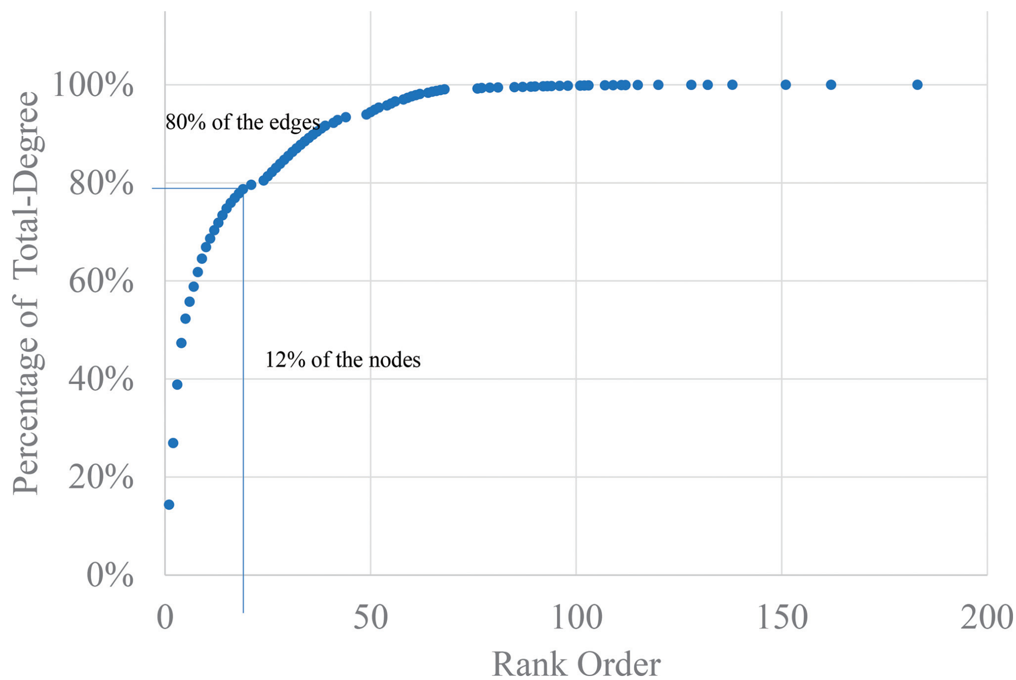

Fig. 1. Percentage of total-degree and rank order.
The rank order of total-degree for each node was plotted on the x-axis and the percentage of total-degree was plotted on the y-axis. In total, 12% of the nodes were responsible for 80% of the edges.

Dynamic network analysis

We used the events and activities shown in Table 1 to identify the ultra-acute phase as the period from the occurrence of flooding to point c (2015/9/30; setting up of a joint headquarters by the mental health team and the Japanese Red Cross). The city hall was restored by that point, and was used for the headquarters. The end of the ultra-acute phase was likely to be before point c, but we could not specify the exact time point. At point d (2015/10/10), the Ibaraki Medical Center for Dementia started to visit older people. Ibaraki Medical Center for Dementia is a permanent local organization with teams working routinely in the

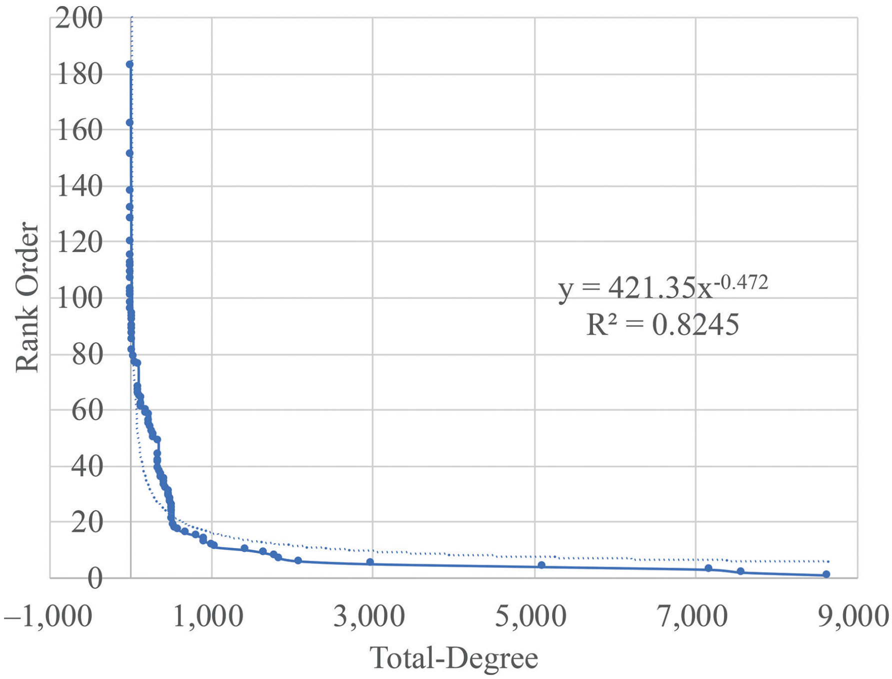

Fig. 2. Total-degree and rank order.
The total-degree of each node was plotted on the x-axis and the rank order of total-degree was plotted on the y-axis, to give a steeper curve. This curve was fitted to a power curve ($y = 421.35x^{-0.472}$, $R^2 = 0.8245$), which indicates that the network has scale-free properties.

area. At point e (2015/10/13), the mental health team stopped working at evacuation centers because several of these centers were closed. The period until points d and e, which was approximately 1 month from the time point at which the flood occurred, was considered to be the acute phase. After the acute phase, the provision of support activity shifted from temporary to permanent local teams.

The average number of nodes was 66.0, the maximum was 103 (during the 7 days from 2015/10/2 1:37), and the minimum was 17 (during the 7 days from 2015/11/28 1:37). Before the network started on 2015/10/16 1:37, there were approximately 80 participants in each network. After the network started on 2015/10/17 1:37, the number of participants gradually decreased, except for a period from 2015/12/1 1:37 to 2015/12/7 1:37, when the number of participants increased to approximately 80 again, as shown in Fig. 3.

The average edge density was 0.089, the maximum was 0.257 (during the 7 days from 2015/11/28 1:37), and the minimum was 0.027 (during the 7 days from 2015/12/7 13:37). As shown in Fig. 4, before the network started on 2015/9/18 1:37, edge density increased gradually. After that, the edge density gradually decreased. From just after the network started on 2015/10/15 1:37, the edge density increased and formed a peak at 2015/10/26 13:37. Edge density was generally flat in the period from 2015/11/3 1:37 to 2016/11/24 1:37, and rose sharply in the period from 2015/11/24 13:37 to 2015/11/30 1:37.

The average transitivity was 0.369, the maximum transitivity was 0.707 (during the 7 days from 2015/11/26 1:37), and the minimum transitivity was 0.078 (during the 7 days from 2015/12/8 13:37). As shown in Fig. 5, 1-month cycles were repeated twice. The first cycle was from 2015/9/10 13:37 to 2015/10/8 1:37, and the second was from 2015/10/8 1:37 to 2015/11/4 1:37. In the period from 2015/11/24 13:37 to 2015/11/30 13:37, transitivity rose and fell steeply.

The average reciprocity was 0.253, the maximum reciprocity was 0.448 (during the 7 days from 2015/11/27 13:37), and the minimum reciprocity was 0.095 (network during the 7 days from 2015/12/7 13:37). As shown in Fig. 6, reciprocity was slightly increased or continued to be flat for 90 days. The reciprocity was particularly high in the period from 2015/11/26 1:37 to 2015/11/30 1:37.

The average assortativity was −0.075, the maximum was 0.105 (during the 7 days from 2015/10/7 1:37), and the minimum was −0.489 (during the 7 days from 2015/11/30 1:37). As shown in Fig. 7, assortativity remained positive but flat from the start of this network to 2015/9/28 1:37. After 2015/9/28, the assortativity swung to negative, but was positive in the periods from 2015/10/6 1:37 to 2015/10/16 13:37, 2015/11/18 13:37 to 2015/11/23 13:37, and 2015/12/7 1:37 to 2015/12/8 1:37.

Visualization of a time series network with cluster analysis

We visualized the time series networks to facilitate understanding the DMHS relationships, as shown in the linked video (https://youtu.be/6AIc8ekEUTA). The movement of the network appeared to fit well with the results of the cluster analysis.

Fig. 3. Time series changes in the number of nodes.
The number of nodes is the number of participants who sent and/or received emails in the network during each window period. The number of nodes represents the size of the network. The start time of each window was plotted on the x-axis and the number of nodes were plotted on the y-axis. The timing of events is shown in Table 1.

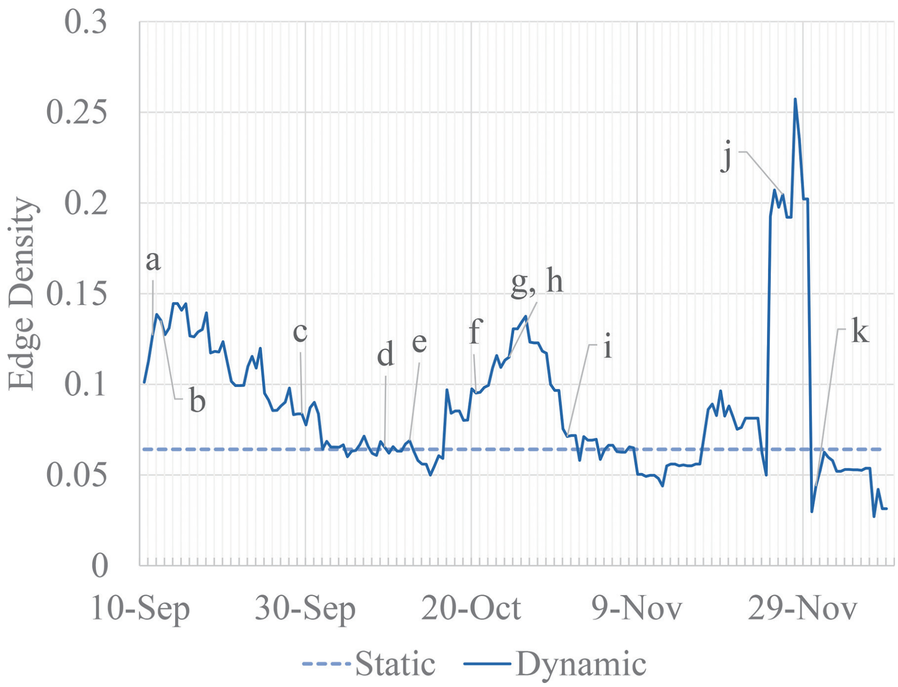

Fig. 4. Time series changes in edge density.
The edge density of the graph is the ratio of the number of edges and the number of possible edges. More complicated networks have a higher density. The start time of each window was plotted on the x-axis and the time series edge density were plotted on the y-axis. The edge density of the static network was plotted as a constant. The timing of events is shown in Table 1.

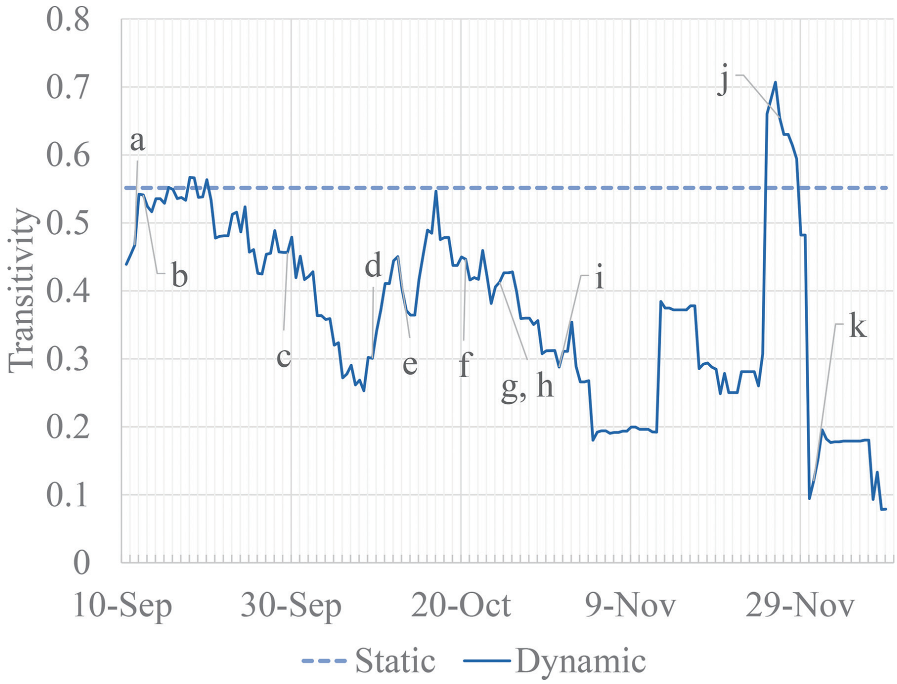

Fig. 5. Time series changes in transitivity.

Transitivity measures the probability that the adjacent nodes are connected. Transitivity reveals the presence of triads (connections between three nodes). The start time of each window was plotted on the x-axis and the time series transitivity were plotted on the y-axis. The transitivity of the static network was plotted as a constant. The timing of events is shown in Table 1.

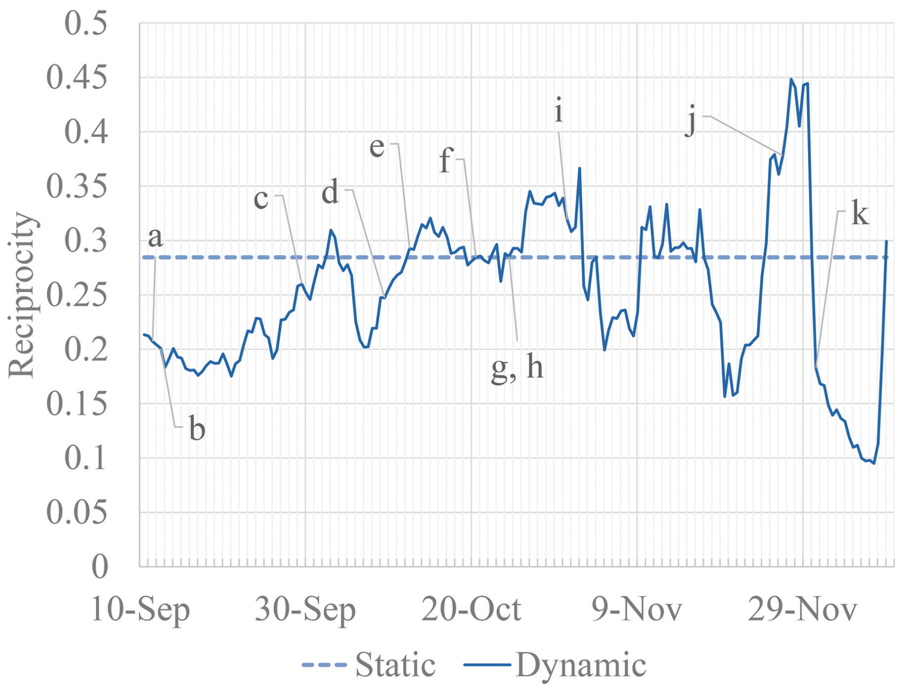

Fig. 6. Time series changes in reciprocity.

Reciprocity indicates the proportion of the edges between two nodes who sent and received emails between each other. High reciprocity of a network represents a high probability of bidirectional exchange of information, not unilateral command. The start time of each window was plotted on the x-axis and the time series reciprocity were plotted on the y-axis. The reciprocity of the static network was plotted as a constant. The timing of events is shown in Table 1.

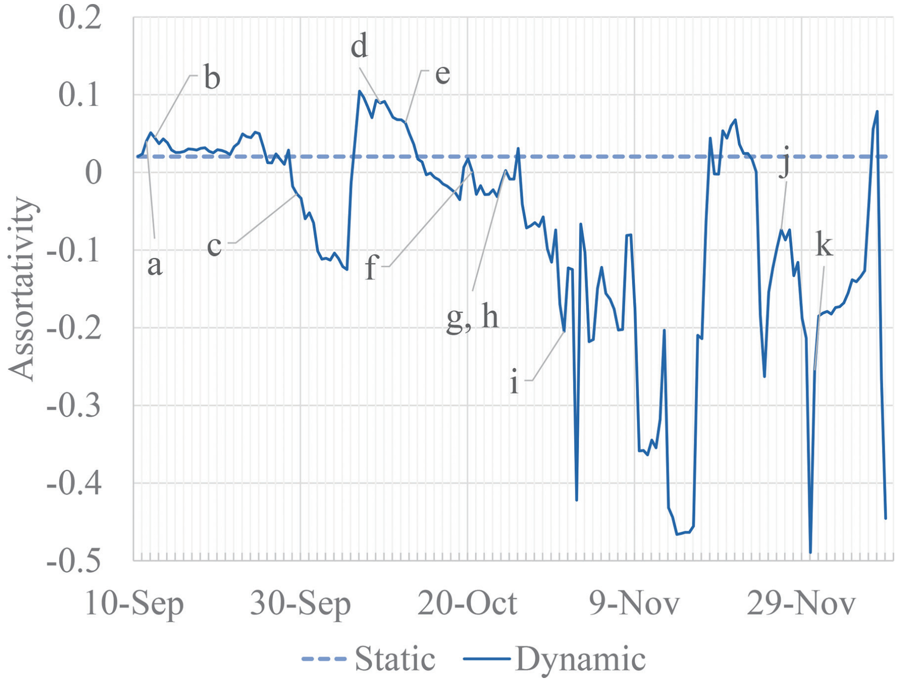

Fig. 7. Time series changes in assortativity.
The assortativity coefficient measures the level of homophily of the graph, based on node degree. In a high assortativity network, high-degree nodes prefer to attach to other high-degree nodes, and low-degree nodes prefer to attach to other low-degree nodes. Conversely, in a low assortativity network, high-degree nodes prefer to attach to other low-degree nodes, and low-degree nodes prefer to attach to other high-degree nodes. The start time of each window was plotted on the x-axis and the time series assortativity were plotted on the y-axis. The assortativity of the static network was plotted as a constant. The timing of events is shown in Table 1.

Discussion

Interpretation of results

To the best of our knowledge, the current study is the first to characterize time series changes of the formation of disaster medical support teams using network analysis of emails. The cluster analysis revealed the structures of the static network and aided visualization of the time series network. We suggest that support arrangements should be modified to fit the changing mental health needs at the disaster site over time. A flexible structure might make it easier for support teams to bring together individuals from a variety of backgrounds, occupations and institutions.

The number of nodes and the edge densities started high and decreased during the acute phase of disaster support. Highly concentrated communication was required in the acute phase when core members of DMHS were selecting and connecting staff and designing a plan. Swift top-down decision-making might result in decreasing density after the acute phase. The number of nodes remained high for a month, while the work needed a structure in which large numbers of staff worked under the direction of the core members. The increasing reciprocity might be caused by the growing consensus of the group about action, and the need to make decisions about long-term support provision. This suggests that provision of long-term support might require more discussion than acute response arrangements.

High transitivity indicated that large numbers of triads were created locally. The establishment of a chain of command might have decreased the number of triads. The increased transitivity in late November may have been related to the counseling team stopping work, and preparations being made for a stress checkup for city employees, because these events required another chain of command.

The network structure was built spontaneously and changed to fit the demands of the site. In the ultra-acute phase, which ran for almost 1 week, the highest priority was spreading information and recruiting members for the disaster support team. In the next month of the acute phase, the most important element was swift decision making to direct staff. Beyond those phases, peer support across small sub-groups may be useful.

The edge density of the time series network exceeded that of the static network during almost all periods. In a larger social network, the edge density is lower because the number of possible edges increases rapidly with number of nodes, but the number of ties that each person can maintain is limited (De Nooy et al. 2011). In other measures, the static network generally exceeded the average for the time series network. Transitivity showed the presence of triads, or connections between three people. When there is a connection between two people (dyad), and a third person adds another connection, this forms a triad. In the relatively short term, there were few triads, but over time, the probability of triads increased. The time series network therefore had lower transitivity than the static network. The communication of nodes became closer, increasing the transitivity. In periods when the transitivity of the time series network was higher than that of the static network, such as from November 25 to November 29, there might have been some sub-groups acting. This tendency fit with the reciprocity. The assortativity coefficient of the static network was positive, which indicates that the static network was assortative, or relatively hierarchical. The average assortativity coefficient of the time series networks, however, was negative. This structure enabled network members to share information on site and function well as an organization.

Comparison with previous work

One of the key principles of disaster response is the use of a command and control structure (Sammut et al. 2001). This functions as a decision-making system for disaster support organizations by creating a multi-echelon hierarchy. Individuals and organizations in this hierarchy tend to exhibit assortativity, because higher-status individuals and organizations prefer to have ties with others of similar status (Benjamin and Podolny 1999; Buchler et al. 2016). In the current study, assortativity remained positive for the first 3 weeks, suggesting strong command and control arrangements during the acute phase of disaster support. Later, the assortativity fluctuated widely, becoming close to negative, which suggests that the organization became disassortative. Buchler et al. (2016) pointed out several major "growing pains" for networked organizations, one of which was assortativity. They noted that information channels and socio-technical limitations could restrict the free flow of information and communications (Bateman 1996). It is not clear how to promote an disassortative organization (Buchler et al. 2016). In the organization examined in the current study, core members with a lot of information passed it by email to other members using mailing lists. The widespread sharing of information made the organization disassortative, which may have been partly what made it so successful in supporting disaster victims.

Limitations

This study involved several limitations that should be considered. We did not collect all emails from all members of the network, so the emails examined may not have reflected the true network. However, because the curve of the distribution of degree fitted the power curve, we considered that this email network was probably extracted from a true scale-free network structure. We did not evaluate the content of the emails, so the effect of the structure on decision-making and support provision was unclear. The outcomes were therefore difficult to evaluate, but support was provided smoothly from the ultra-acute phase into the long term without any major difficulties. Widespread sharing of information by network members caused the organization to become disassortative, which may be a better way to achieve a useful organizational structure. There was, however, an imbalance in information sharing, because a few core members dominated this process, and most members of the network had very few email connections. If all information is shared, some individuals may receive emails that are beyond their functional cognitive capacity to process (Buchler et al. 2016). If shared information contains private information, it is important to control sharing more strictly.

It is important to consider the use of alternatives in digital communication, including fast digital messaging services or social networking services. These media tools can play a role in improving the immediacy of communication and the sharing of information. Sometimes new media can offer information to the general public, by connecting the network to the public. Future studies will be needed to investigate the communication networks created by mixed media.

Conclusion

Our research used network analyses to show the time series changes in structure among a DMHS. The results suggest that disaster support arrangements should be modified to fit with the changing medical needs of the site over time. In the ultra-acute stage, which lasted approximately 1 week, spreading information and recruiting staff were the highest priorities. In the acute phase, swift decision-making to direct staff was more important. After these phases, it may be most important to encourage peer support in small sub-groups. Although the results were derived from DMHS activities, the key findings in our study are applicable to organizing any type of DMT.

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Author Contributions

Y.S. conducted network analyses, drafted the initial manuscript, and revised the manuscript. H.T. and K.N. conceptualized and designed the study, collected data, and revised the manuscript.

I.M., S.T. and T.H. collected data and revised the manuscript. N.S. and M.T. conducted network analyses and reviewed and revised the manuscript. T.A. conceptualized and designed the study, collected data, and reviewed and revised the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

References

Advanced Life Support Group (2011) *Major incident medical management and support: The practical approach at the scene*, 3rd ed., Wiley-Blackwell, Oxford, UK.

Arziman, I. (2015) Field organization and disaster medical assistance teams. *Turk. J. Emerg. Med.*, **15**, 11-19.

Barabási, A.L., Albert, R. & Jeong, H. (1999) Mean-field theory for scale-free random networks. *Physica A*, **272**, 173-182.

Bateman, R.L. (1996) Force XXI and the death of Auftragstaktik. https://apps.dtic.mil/dtic/tr/fulltext/u2/a323301.pdf [*Accessed*: September 17, 2020].

Benfield, A. (2018) Weather, climate & catastrophe insight: 2017 annual report. https://reliefweb.int/sites/reliefweb.int/files/resources/20180124-ab-if-annual-report-weather-climate-2017.pdf [*Accessed*: September 17, 2020]

Benjamin, B.A. & Podolny, J.M. (1999) Status, quality, and social order in the California Wine Industry. *Adm. Sci. Q.*, **44**, 563-563.

Bollobás, B. (1998) *Modern graph theory*, Springer, NY, USA.

Buchler, N., Fitzhugh, S.M., Marusich, L.R., Ungvarsky, D.M., Lebiere, C. & Gonzalez, C. (2016) Mission command in the age of network-enabled operations: social network analysis of information sharing and situation awareness. *Front. Psychol.*, **7**, 937.

Clauset, A., Moore, C. & Newman, M.E. (2008) Hierarchical structure and the prediction of missing links in networks. *Nature*, **453**, 98-101.

Dai, W., Kaminga, A.C., Tan, H., Wang, J., Lai, Z., Wu, X., Xiong, Y., Deng, J. & Liu, A. (2017) Comorbidity of post-traumatic stress disorder and anxiety in flood survivors: prevalence and shared risk factors. *Medicine* (*Baltimore*), **96**, e7994.

De Nooy, W., Mrvar, A. & Batagelj, V. (2011) *Exploratory social network analysis with Pajek*, Cambridge University Press, UK.

Fontalba-Navas, A., Lucas-Borja, M.E., Gil-Aguilar, V., Arrebola, J.P., Pena-Andreu, J.M. & Perez, J. (2017) Incidence and risk factors for post-traumatic stress disorder in a population affected by a severe flood. *Public Health*, **144**, 96-102.

Fortunato, S. (2009) Community detection in graphs. *Physics Reports*, **486**, 75-174.

Fuse, A. & Yokota, H. (2010) An analysis of Japan Disaster Medical Assistance Team (J-DMAT) deployments in comparison with those of J-DMAT's counterpart in the United States (US-DMAT). *J. Nippon Med. Sch.*, **77**, 318-324.

Geographical Survey Institute of Japan (2015) Joso flood. http://mapps.gsi.go.jp/contentsImageDisplay.do?specificationId=1647551&isDetail=false [*Accessed*: April 18, 2020].

Hasan, S., Bonde, B.K., Buchan, N.S. & Hall, M.D. (2012) Network analysis has diverse roles in drug discovery. *Drug Discov. Today*, **17**, 869-874.

Kinnison, J., Padmala, S., Choi, J.M. & Pessoa, L. (2012) Network analysis reveals increased integration during emotional and motivational processing. *J. Neurosci.*, **32**, 8361-8372.

Kolli, N. & Narayanaswamy, B. (2013) Analysis of e-mail communication using a social network framework for crisis detection in an organization. *Procedia-Social & Behavioral Sciences*, **100**, 57-67.

Lebowitz, A., Tachikawa, H., Aiba, M., Okamoto, Y., Takahashi, S., Nemoto, K. & Arai, T. (2019) Post-flood social support networks and morbidity in Joso City, Japan. *Psychiatry Res.*, **271**, 708-714.

Liu, Y., Koyuturk, M., Barnholtz-Sloan, J.S. & Chance, M.R. (2012) Gene interaction enrichment and network analysis to identify dysregulated pathways and their interactions in complex diseases. *BMC Syst. Biol.*, **6**, 65.

Matthews, L.J., DeWan, P. & Rula, E.Y. (2013) Methods for inferring health-related social networks among coworkers from online communication patterns. *PLoS One*, **8**, e55234.

Newman, M.E.J. (2002) Assortative mixing in networks. *Phys. Rev. Lett.*, **89**, 208701.

Newman, M.E.J. (2004) Power laws, Pareto distributions and Zipf's law. *Contemp. Phys.*, **46**, 323-351.

North, C.S. & Pfefferbaum, B. (2013) Mental health response to community disasters: a systematic review. *JAMA*, **310**, 507-518.

Oldham, M.C., Langfelder, P. & Horvath, S. (2012) Network methods for describing sample relationships in genomic datasets: application to Huntington's disease. *BMC Syst. Biol.*, **6**, 63.

Pfefferbaum, B., Flynn, B.W., Schonfeld, D., Brown, L.M., Jacobs, G.A., Dodgen, D., Donato, D., Kaul, R.E., Stone, B., Norwood, A.E., Reissman, D.B., Herrmann, J., Hobfoll, S.E., Jones, R.T., Ruzek, J.I., et al. (2012) The integration of mental and behavioral health into disaster preparedness, response, and recovery. *Disaster Med. Public Health Prep.*, **6**, 60-66.

Sammut, J., Cato, D. & Homer, T. (2001) Major Incident Medical Management and Support (MIMMS): a practical, multiple casualty, disaster-site training course for all Australian health care personnel. *Emerg. Med.* (*Fremantle*), **13**, 174-180.

Scott, J. & Carrington, P.J. (2011) *The SAGE handbook of social network analysis*, SAGE Publishing, NY, USA.

Shiratori, Y., Tachikawa, H., Nemoto, K., Endo, G., Aiba, M., Matsui, Y. & Asada, T. (2014) Network analysis for motives in suicide cases: a cross-sectional study. *Psychiatry Clin. Neurosci.*, **68**, 299-307.

Strogatz, S.H. (2001) Exploring complex networks. *Nature*, **410**, 268-276.

Tashiro, H., Mori, J., Fujii, N. & Matsushima, K. (2010) Email network analysis for organizational management tool. *IEEE*, ICMIT2010.

Wuchty, S. & Uzzi, B. (2011) Human communication dynamics in digital footsteps: a study of the agreement between self-reported ties and email networks. *PLoS One*, **6**, e26972.

Xiao Fan, W. & Guanrong, C. (2003) Complex networks: small-world, scale-free and beyond. *IEEE Circuits and Systems Magazine*, **3**, 6-20.

Yoda, T., Yokoyama, K., Suzuki, H. & Hirao, T. (2017) Relationship between long-term flooding and serious mental illness after the 2011 flood in Thailand. *Disaster Med. Public Health Prep.*, **11**, 300-304.