Social Network Analysis of Multisector Stakeholder Collaboration and Engagement in Housing Resilience Planning

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ABSTRACT

Housing resilience planning is a dynamic process that involves multisector stakeholders, including public agencies, private industries, nongovernment organizations (NGOs), academia, and community residents. Despite the importance of multisector stakeholder collaboration, there is limited understanding of stakeholder collaboration in housing resilience planning. To address this gap, this study analyzes how multisector stakeholders collaborate in producing housing resilience-focused plans, reports, and guidelines utilizing social network analysis (SNA). A two-mode, stakeholder-document, SNA model was built based on secondary data collected from 39 documents on housing resilience in three regions, including the City of Miami, the City of Miami Beach, and Miami-Dade County. The network analysis shows that there are significant differences in network measures across different stakeholder sectors. The findings from this study could offer insights on how to facilitate more effective and collaborative housing resilience planning.

INTRODUCTION

Over the last few decades, the world has witnessed a growing intensity and frequency of natural hazards, including floods, droughts, hurricanes, and earthquakes (UNISDR 2012). Coastal areas, such as the Greater Miami and the Beaches (GM&B), are becoming especially vulnerable to disasters due to their physical vulnerabilities and dense population (GM&B 2019). To deal with the catastrophic impacts of disasters, planning and implementing disaster resilience policies could help the communities prepare for, absorb, adapt to, and recover from actual or potential disasters in a timely and efficient manner (Taeby and Zhang 2019). However, disaster resilience planning is a challenging task because it is a shared responsibility that requires active participation and collaboration of all relevant stakeholders. These stakeholders could be from multiple sectors, including governments, private industries, nongovernment organizations (NGOs), universities, and community leaders (Kapucu and Garayev 2011). Collaborations across multisector stakeholders with different backgrounds are expected to increase knowledge sharing, improve situational awareness and policymaking, and enhance community cohesion, which would lead to better solutions to disaster resilience problems (Taeby and Zhang 2019).

Although the importance of multisector stakeholder collaboration has been emphasized in the interdisciplinary disaster resilience literature, there are limited studies that focus on understanding how these stakeholders are involved in resilience planning. For example, Kapucu and Garayev (2011) stressed the importance of collaborative decision making in emergency and disaster management and identified several factors (e.g., timely communication tools, the flexibility of representatives) that could improve collaborative decision making. Ganapati and Mukherji (2014) noted the significance of closer collaboration among different agencies for disaster management activities, such as shelter provision. Pyke et al. (2018) highlighted that stakeholder engagement and collaboration are important to build a resilient city. In addition, there are a number of studies that explore different approaches to facilitating stakeholder collaboration in a disaster context. For instance, Zhang et al. (2019) proposed a stakeholder value aggregation model to facilitate collaborative decision making on disaster resilience by using a reinforcement learning-based method. Pathak et al. (2020) explored and offered an understanding of the stakeholder values and value priorities across different phases of Hurricane Michael in Florida to facilitate engagement and collaboration in building resilient communities.

To address the above-mentioned gap, this paper uses Social Network Analysis (SNA) to analyze how multisector stakeholders collaborate and contribute to housing resilience planning. An SNA model was built based on the data collected from 39 documents on housing resilience planning in three regions, including the City of Miami, the City of Miami Beach, and Miami-Dade County in Florida, USA. Network analysis measures were used to offer a quantitative understanding of the level of collaboration and involvement among different stakeholder sectors. The remainder of the paper reviews the relevant work on social network analysis, introduces the methodology, presents and discusses about the results, and concludes with a summary of the study.

SOCIAL NETWORK ANALYSIS (SNA)

SNA explores social networks based on graph theories. A social network model is constructed with nodes (e.g., actors, events) and links (e.g., interactions, relationships, affiliations). SNA is a broad class of methods that account for observational dependencies often ignored by traditional statistics, which can be used to describe the patterns and structures of social relationships, explain the drivers of social interactions, and contribute to the analysis of other variables of interest. This methodology has been applied in many research fields in the last few decades, such as political science, public policy and administration (e.g., Provan and Kenis 2008), biology, and public health (e.g., Horvath 2011). It has also become increasingly popular in the civil engineering domain, such as transportation planning (e.g., Vechan et al. 2014) and construction management (e.g., Gan et al. 2018). In recent years, SNA has been used in disaster-related studies as well. For example, Sadri et al. (2017) used SNA to analyze the evacuation decision-making behaviors during Hurricane Sandy. Fan et al. (2019) integrated SNA to develop strategies for disseminating information in online social networks during Hurricane Harvey. Rouhanizadeh and Kermanshachi (2019) used SNA to investigate the relationships of socioeconomic factors that delay post-disaster reconstruction. Despite a growing number of disaster studies utilizing the SNA, there are currently limited studies that focus on using SNA to analyze multisector stakeholder collaboration in housing resilience planning. SNA can provide a powerful quantitative understanding of network structures and measures of multisector stakeholder collaboration.

RESEARCH METHODOLOGY

The research methodology has the following five main steps:

Establishing a conceptual SNA model. This step is aimed at developing a conceptual SNA model to analyze the collaboration and involvement of multisector stakeholders in developing housing resilience plans, reports, and guidelines (referred to as the documents hereafter). In the proposed SNA model, there are two sets of nodes. One set of nodes represent the planning documents, and the other set of nodes represent the stakeholders who are involved in developing each document. A tie or an edge was established between a stakeholder and a document to indicate the involvement of the stakeholder in developing the document. This kind of network is known as the two-mode network or affiliation network in network science.

Collecting social network data. To collect the data for the nodes and ties of the proposed network, we systematically reviewed documents published on the governments' websites, including the websites of all the offices or departments of the City of Miami, City of Miami Beach, and Miami-Dade County. These regions were selected because they are vulnerable to several types of natural hazards, such as hurricanes, flooding, and sea-level rise, and they were selected to join the 100 Resilient City Program by the Rockefeller Foundation to plan a set of initiatives for improving the resilience of local communities. The following inclusion criteria were used during the systematic review: (1) the types of the documents are plans, reports, or guidelines; (2) the topics of the documents are related to "housing and disaster" or "housing resilience", (3) the publication year of the documents are from the year 2010 to 2021. A total of 39 documents were collected by applying these criteria.

Coding and visualizing network. After collecting all the documents, the nodes and ties of the SNA model were coded. To code the first set of nodes, all the titles of documents were extracted and tabulated using the abbreviations of the titles. To code the second set of nodes, the names of the stakeholders that contributed to the development of each document were identified and tabulated with abbreviations. In this study, the stakeholders were classified into five different groups for analysis, including public agencies, private industries, NGOs, academia, and community residents. The ties were the affiliation relationships between the stakeholders and the documents. The network was then created through Gephi, which is a powerful network visualization and analysis software.

Determining network measures. Three different network measures were used to analyze the model, including degree centrality, eigenvector centrality, and betweenness centrality. Degree centrality (Eq. 1) measures the number of direct ties that a focal node is connected to. It is used to show the popularity or importance of a node (Freeman 1978; Newman 2008).

$$C_d(i) = \sum_{j=1}^{N} x_{ij} \tag{1}$$

where $C_d(i)$ is the degree centrality of node i; i represents the focal node and j represents another node; x_{ij} is the binary adjacency matrix, where the value of x_{ij} is 1 if node i is directly connected to node j, otherwise it is 0; and N is the total number of nodes in the network.

Compared to degree centrality, eigenvector centrality (Eq. 2) further considers the influence of nodes that a focal node is connected to. Eigenvector centrality acknowledges that a focal node is more influential when the neighboring nodes themselves are more influential (Newman 2008).

$$C_{ev}(i) = \frac{1}{\lambda} \sum_{j=1}^{N} x_{ij} C_{ev}(j) \tag{2}$$

where $C_{ev}(i)$ is the eigenvector centrality of node i ; λ is a constant; x_{ij} is the binary adjacency matrix; $C_{ev}(j)$ is the eigenvector centrality of node j; and N is the total number of nodes in the network.

Betweenness centrality (Eq. 3) is a network measure that accounts for the shortest path of the whole network. It measures how often a node lies on the shortest path between two other nodes (Freeman 1978). Nodes with high betweenness centrality are considered to have high influence or control over information flow.

$$C_b(i) = \sum \frac{g_{jk}(i)}{g_{jk}}, i \neq j \neq k \tag{3}$$

where $C_b(i)$ is betweenness centrality of node i; g_{jk} is the number of shortest paths between node j and node k; and $g_{jk}(i)$ is the number of those paths that goes through node i.

Analyzing the differences. After determining the network measures for the five sectors of stakeholders, the Kruskal-Wallis H test was conducted to assess whether there were significant differences across different stakeholder sectors. Kruskal-Wallis H test is a nonparametric test that is typically used for comparing the differences among three or more independent samples (LAERD 2021). The results of the test were interpreted through the probability value (p-value). If the p-value is less than 0.05, there are significant differences across different sectors. Post-hoc pairwise comparison tests (i.e., Mann-Whitney U-tests with a Benjamini and Hochberg correction) were then performed to test which pair of stakeholder groups were significantly different.

RESULTS

Network mapping. Figure 1 shows the complete map of the two-mode network model, in which the green nodes represent the collected documents, and the other five colors represent the stakeholders from five different sectors. There are a total of 305 nodes and 476 ties identified in this network. Among the nodes, 266 of them are stakeholders. There are 81 stakeholders from public agencies (red nodes), 80 stakeholders from private industries (blue nodes), 90 stakeholders from NGOs (brown nodes), 10 stakeholders from academia (light blue nodes), and 5 stakeholders representing community residents (pink nodes). The size of each node is based on the degree centrality of the node.

As per Figure 1, there are relatively large numbers of public, private, and NGO stakeholders contributing to housing resilience planning. In contrast, the numbers of stakeholders from academia and community residents are relatively small. Based on the size (degree centrality) of the nodes in Figure 1, Miami-Dade County, the City of Miami, the City of Miami Beach, the City of Miami Garden, and North Bay Village are the public stakeholders that contribute the most to the development of the documents. Florida Power & Light and JPMorgan Chase companies are the most engaged private stakeholders. Catalyst Miami, South Florida Community Development Coalition, and Miami Homes for All are the NGOs who were involved more in preparing for resilience-focused documents. Academic stakeholders, such as the University of Miami, Florida International University, Miami Dade College, and the University of Florida were found to have more contributions to these documents. It is worth noticing that except for the University of Florida, all these universities are located in South Florida.

Analysis of Network Measures. Network analysis was conducted to analyze the two-mode social network model. The results of the three network measures, including average degree centrality, average eigenvector centrality, and average betweenness centrality of the five sectors of stakeholders are summarized in Table 1.

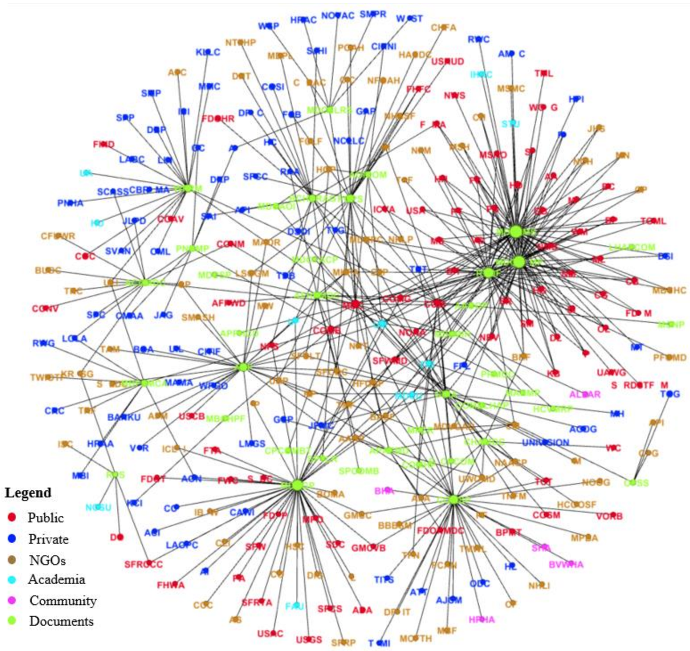

Figure 1. Network map.

As per Table 1, academic and public stakeholders have higher average values (3.100 and 2.580, respectively) in degree centrality, followed by the NGOs and private industries. By average, academic and public stakeholders have higher number of ties or connections to these planning documents. The results imply that public and academic stakeholders tend to contribute more to housing resilience planning, making themselves more influential and experienced in the whole network. On the other hand, community residents have the lowest value (1.000) in degree centrality, indicating that each community is likely to contribute to only one planning document.

The results in Table 1 also show that the stakeholders from public agencies have the highest average values in eigenvector centrality, compared to private industries, NGOs, and community residents. This implies public stakeholders are more likely to contribute to more important planning documents, thus playing the most influential role in housing resilience planning. In contrast, community residents have the lowest values in eigenvector centrality, indicating their least influential role in the network.

In terms of betweenness centrality, the results show that stakeholders from academia have the highest value of 695.130 among all the sectors. This indicates that academic stakeholders have a high control power of bridging the information flows in the social network and preventing network fragmentation or network closure. Stakeholders from public agencies have a relatively higher value of 387.471. In contrast, the value of betweenness centrality for community residents is 0.000, which indicates that community residents have no control power over the information exchange. It implies that the participation and influence of community residents are insufficient.

Kruskal-Wallis H tests were further performed to determine if there were significant differences among different stakeholder sectors for each centrality measure. The p-values for all network measures are less than 0.05, indicating that there are significant differences in the centrality measures among different sectors of stakeholders. Subsequently, pairwise comparisons were performed to test which pairs of sectors are significantly different. The results of pairwise comparisons are shown in Table 2. As per Table 2, the post-hoc pairwise comparisons revealed that statistically significant differences between different pairs of stakeholder groups follow similar patterns in the three network measures, and the significant differences can be observed between public and private stakeholders, public stakeholders and NGOs, public stakeholders and community residents, private stakeholders and NGOs, and private and academic stakeholders.

Table 1. Results of Network Measures

Sectors	Average Degree Centrality	Average Eigenvector Centrality	Average Betweenness Centrality
S1	2.580	0.120	387.471
S2	1.125	0.018	13.984
S3	1.567	0.033	68.820
S4	3.100	0.095	695.130
S5	1.000	0.009	0.000

[a]S1 = public agencies, S2 = private industries, S3 = NGOs, S4 = academia, S5 = community residents

Table 2. Results of Post-Hoc Pairwise Comparisons

Pairwise Combinations[a]	Degree Centrality	Eigenvector Centrality	Betweenness Centrality
S1 vs S2	0.000[b]	0.000[b]	0.000[b]
S1 vs S3	0.001[b]	0.000[b]	0.025[b]
S1 vs S4	0.871	0.337	0.732
S1 vs S5	0.039[b]	0.008[b]	0.042[b]
S2 vs S3	0.001[b]	0.000[b]	0.001[b]
S2 vs S4	0.001[b]	0.036[b]	0.001[b]
S2 vs S5	0.524	0.384	0.525
S3 vs S4	0.162	0.200	0.151
S3 vs S5	0.162	0.337	0.165
S4 vs S5	0.134	0.221	0.134

[a]S1 = public agencies, S2 = private industries, S3 = NGOs, S4 = academia, S5 = community residents
[b]The p-value is significant at 0.05 level.

DISCUSSION

Network measure results show that, in general, stakeholders from public agencies and academia play more important roles and have a higher control power of information flow in resilience planning. This may be because the public agencies have stronger public responsibilities and often play the leading roles in resilience planning. For stakeholders from academia, they possess the relevant professional knowledge, expertise, and research experiences, which are essential for effective resilience planning. The high centrality of academic institutions suggests a positive collaborative environment for decision making which incorporates multiple epistemic perspectives toward the resolution of complex public problems (Raadschelders and

Whetsell 2018). Stakeholders from the NGOs and the private industries are also relatively active in housing resilience planning. The goal of housing resilience is aligned with the vision of several NGOs, such as Miami Homes for All and Catalyst Miami. The study also finds that the involvement of community residents is insufficient. Further investigations of the contents of the documents identified that community residents are typically not formally acknowledged as contributing to the development of the documents, and the discussion of community engagement is usually vague. Although community engagement is a time- and effort-consuming process, it is very important to systematically engage community residents as they may provide valuable inputs from the standpoints of impacted stakeholders (i.e., stakeholders who are affected by the resilience initiatives). In addition, engaging community residents will further empower them to become more informed and supportive of resilience initiatives or investments.

The study also finds that there are significant differences in the network measures across different sectors of stakeholders. While it is expected that different stakeholder sectors have different levels of contributions to housing resilience planning, an ideal network would allow more balanced or equal contributions from multisector stakeholders. This would allow stakeholders from multiple sectors to form a more inclusive collaboration mechanism, which may eventually support the development of resilience initiatives that benefit all stakeholders.

CONCLUSIONS

This paper analyzes the multisector stakeholder collaboration on housing resilience planning in the region of GM&B (including the City of Miami, the City of Miami Beach, and Miami-Dade County). By collecting the relevant data from the plans, reports, and guidelines in this region, a two-mode, stakeholder-document, SNA model was built. The results show that there are significant differences in network measures among public agencies, private industries, NGOs, academia, and community residents. This research finds that public agencies and academic stakeholders have contributed more to housing resilience planning, while the involvements of community residents are insufficient. Thus, systemically engaging community residents is important to facilitate stakeholder collaborations in future housing resilience planning. The findings from this study could offer insights on how to better facilitate housing resilience planning through multisector stakeholder collaboration and public engagement. In the future, the authors will further explore network interactions by analyzing tie weights, as well as exploring the relationships between node centrality and other organization-level variables of interest. Other network analysis approaches (e.g., exponential random graph models) will also be explored to offer a more robust understanding of the drivers of stakeholder collaboration.

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