Analyzing Multisector Stakeholder Collaboration and Engagement in Housing Resilience Planning in Greater Miami and the Beaches through Social Network Analysis

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Abstract: Housing resilience planning is a challenging process that requires active participation of multisector stakeholders, including public agencies, private industries, nongovernmental organizations (NGOs), academia, and community residents. Despite the importance of multisector stakeholder collaboration and engagement, there is limited understanding of how stakeholders collaborate and engage in housing resilience planning. To address this gap, this study used social network analysis (SNA) to analyze how multisector stakeholders collaborate in producing housing resilience-focused plans, reports, and guidelines. A bipartite SNA model was built based on the data collected from 39 housing resilience planning documents in the Greater Miami and the Beaches (GM&B) region, including the City of Miami, the City of Miami Beach, and Miami-Dade County. Three network centrality measures were computed, and exponential random graph model (ERGM) analysis was performed to analyze the network. This study found that there are significant differences in the centrality measures across different stakeholder sectors. Among them, public agencies and academic stakeholders contributed more to housing resilience planning, whereas the involvement of community residents was relatively limited compared with that of the other sectors. In addition, the results suggest that more-balanced, decentralized, and intersector collaboration mechanisms may be needed to enhance housing resilience planning. The findings from this study offer knowledge of and insight into how to facilitate more-effective multisector stakeholder collaboration in planning for housing resilience. **DOI: 10.1061/(ASCE)NH.1527-6996.0000594.** *© 2022 American Society of Civil Engineers.*

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Introduction

Over the last few decades, the growing intensity and frequency of natural hazards, including floods, droughts, hurricanes, and earthquakes, have become a global concern to human society (UNISDR 2012). Incorporating housing resilience planning into cities' development is one of the critical strategies to help communities prepare for, respond to, and recover from actual or potential natural hazards. However, resilience planning is a challenging task because it requires effective engagement and collaboration among multisector stakeholders, including public agencies, private industries, nongovernmental organizations (NGOs), academia, and community residents (Kapucu and Garayev 2011; Taeby and Zhang 2019; Gosain et al. 2022). According to *Presidential Policy Directive-8: National Preparedness* (The White House 2011), every sector, not just government, should be involved in a systematic manner to keep the nation safe and resilient when struck by natural hazards. The FEMA Strategic Plan (FEMA 2018, p. 9) pointed out that "one lesson we learned from the catastrophic 2017 hurricane season is that no one department or agency can undertake this effort alone." There has been an increasing need to integrate stakeholders from multiple sectors in the predisaster collaboration to improve the resilience of communities (FEMA 2018). Multisector stakeholder collaboration and engagement could provide a platform that brings people together to reflect the opinions of different parties. It also could increase knowledge sharing and facilitate effective disaster planning strategies toward building a resilient community (Djalante 2012; Sitas et al. 2016; Pathak et al. 2020).

Although the importance of multisector stakeholder collaboration has been recognized widely in the disaster literature, there currently are few studies that focused on understanding how different sectors of stakeholders are involved in the resilience planning processes. Over the last two decades, many research studies (e.g., Chang et al. 2008; Kapucu and Garayev 2011; Ganapati and Mukherji 2014; Burnside-Lawry and Carvalho 2016; Pyke et al. 2018) have highlighted the importance and urgency of engaging stakeholders from different backgrounds to support the development of resilient communities. These studies emphasized that effective stakeholder collaboration is one of the key factors that enhance the resilience of communities in response to disasters (Djalante 2012; Gimenez et al. 2017; Marana et al. 2018; Berke et al. 2021). Many researchers (e.g., Li et al. 2014; Sitas et al. 2016; Desportes et al. 2016; Zhang et al. 2019; Pathak et al. 2020; Li et al. 2021) proposed

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various approaches to facilitate the engagement and collaborations among multisector stakeholder groups in disaster contexts. However, to our knowledge, these studies have not offered a systematic examination of the status of stakeholder collaboration and/or involvement in the disaster resilience planning process.

To address the knowledge gap, this research analyzed how multisector stakeholders collaborate and contribute to housing resilience planning using social network analysis (SNA). SNA investigates the patterns of social relationships and interactions among actors in a bounded social system, and it has been applied in various research areas in the last few decades, such as political science (e.g., Kleinnijenhuis and de Nooy 2013; Xiong et al. 2021), public policy and administration (e.g., Provan and Kenis 2008), biology (e.g., Horvath 2011), agriculture (e.g., Hermans et al. 2017), healthcare (e.g., Pow et al. 2012), and civil engineering areas (e.g., Vechan et al. 2014; Sadri et al. 2017). This research applied SNA to address the following research questions:

R1: Which sector of stakeholders is the most influential (or the least influential) in housing resilience planning processes?

R2: Are there significant differences across different stakeholder sectors in contributing to housing resilience planning?

R3: Is the multisector stakeholder collaboration system centralized or decentralized in housing resilience planning?

R4: What forms of stakeholder collaboration (e.g., intrasector collaboration or intersector collaboration) are more dominant in housing resilience planning?

This study focused on an area of South Florida referred to as the Greater Miami and the Beaches (GM&B) region. This region was selected because it is especially sensitive to housing resilience issues due to its exposure to multiple natural hazards (e.g., flooding, hurricanes, and sea-level rise) and social stresses and crises (e.g., social inequalities and affordability). In this study, first, a bipartite SNA model was built based on the data collected from 39 documents related to housing resilience planning in the GM&B region, including the City of Miami, the City of Miami Beach, and Miami-Dade County in Florida. Second, network centrality measures, including degree centrality, eigenvector centrality, and betweenness centrality, were computed to describe the structure of the network and the positions of the stakeholders. Third, a bipartite exponential random graph model (ERGM) was built based on the observed SNA model to estimate the drivers of tie formation in the network. The results show that there are significant differences in the centrality measures across the five stakeholder sectors. Public agencies and academic stakeholders contributed more to housing resilience planning, whereas the involvement of community residents was relatively limited compared with that of the other sectors. In addition, the results show that centralized and intrasector collaboration is more dominant in housing resilience planning, which may suggest that decentralized and/or intersector collaboration mechanisms are needed. The findings from this study could help facilitate more-effective and collaborative housing resilience planning.

The remainder of the paper reviews the relevant literature and identifies the knowledge gaps; explains the research context and methodology; presents and discusses the results; and concludes with a summary of the study, contributions, and future recommendations.

Literature Review of Multisector Stakeholder Collaboration in Disasters

Many areas across the world are exposed to a variety of disaster risks. Coastal areas, in particular, are subject to various climate change–induced risks and hazards (e.g., extreme weather, sea-level rise, and flooding) (Boyd and Juhola 2015). The increasing frequency and intensity of these risks require our communities to plan for resiliency. Resilience is defined as the ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions (The White House 2013). The concept of resilience has become increasingly popular among policymakers and academics. To facilitate community resilience, it is imperative to integrate resilience with housing planning to deal with uncertainties and complexities due to both rapid- and slow-onset disasters. The importance of integrating resilience with housing planning has been emphasized by many studies (e.g., Jones 2017; Gosain et al. 2022; Sen et al. 2021). There also is a growing recognition that resilience planning should not be led only by governments, but rather should be co-led by governments and nongovernmental stakeholders together (Tierney 2012; Coaffee and Lee 2016). According to the National Oceanic and Atmospheric Administration (NOAA 2015), stakeholders are defined as those who have an interest in or are affected by a decision. In our study, we defined stakeholders as the groups or organizations who are responsible for, impacted by, or interested in resilience planning processes. These stakeholders include public agencies, private industries, NGOs, academia, and community residents. Resilience planning for housing is a challenging task because it is a complex social issue that requires dynamic and active participation and collaboration of various stakeholders (Marana et al. 2018; Ganji et al. 2019).

The benefits and challenges of multistakeholder collaboration are well recognized in the literature (e.g., Kapucu and Garayev 2011; Sitas et al. 2016; Gerkensmeier and Ratter 2018). Multisector stakeholder collaboration involves the joint participation of stakeholders from different sectors to work together and integrate each sector's interests and values to solve complex problems. By openly discussing and acknowledging different sectors' needs and concerns, multisector stakeholder collaboration can largely reduce potential conflicts during decision-making processes (Waugh and Streib 2006; Kapucu and Garayev 2011; Zhang et al. 2019). In addition, effective collaboration is expected to enhance social learning if stakeholders from different sectors are able to inform and/or learn from each other about their knowledge of resilience planning (Keen et al. 2005; Reed et al. 2010). More importantly, multisector stakeholder collaboration facilitates trust among different stakeholders. Building trust among various stakeholders will make them more likely to form connections in the future to collectively respond to disaster risks (Desportes et al. 2016). However, a number of challenges have been identified for multisector stakeholder collaboration in resilience planning, such as difficulty in identifying appropriate stakeholders to be involved in planning processes, ineffective communication and information sharing, inappropriate distribution of resources (e.g., skills and funding), and lack of leadership (Desportes et al. 2016; Ishiwatari 2019).

To address these challenges, extensive studies have been conducted on facilitating stakeholder collaboration in various disaster contexts, such as floods (e.g., Desportes et al. 2016; O'Donnell et al. 2018; Ishiwatari 2019), earthquakes (e.g., Orchiston and Higham 2014; Xu and Lu 2018; Jayasinghe et al. 2020), wildfires (e.g., Fischer et al. 2016; Errett et al. 2019; Charnley et al. 2020), volcanos (e.g., Cronin et al. 2004; Texier-Teixeira et al. 2014), and hurricanes (e.g., Li et al. 2020; Pathak et al. 2020; Dunning 2020). The majority of these studies focused on exploring stakeholder collaboration in the context of disaster response or recovery, and placed less focus on long-term mitigation or resilience planning. For example, Simo and Bies (2007) explored nonprofits' involvement in cross-sector collaborative efforts in the response phase of Hurricane Katrina and Rita. Kapucu (2014) used the National

Disaster Recovery Framework (NDRF) (FEMA 2010) as an example to explore the application of the principle of collaborative governance in disaster recovery. Jiang and Ritchie (2017) investigated stakeholders' motivations for collaboration, factors that facilitate or impede stakeholder collaboration, and successful elements and challenges for effective collaboration in the context of tourism disaster recovery. Lu et al. (2018) investigated multisector stakeholder collaboration in postdisaster reconstruction through case studies of the Longmen Shan fault area in China and the response to earthquakes. Curnin and O'Hara (2019) explored the barriers and enablers of interorganizational collaboration between the nonprofit and public sectors during disaster recovery efforts after a flooding event through in-depth interviews.

In addition, many studies (e.g., Desportes et al. 2016; Sitas et al. 2016; Foley et al. 2017; Pathak et al. 2020; Li et al. 2021) have introduced new approaches to facilitate multisector stakeholder collaboration in response to disasters. However, those studies did not focus on analyzing the existing collaboration conditions among the stakeholders. For example, Desportes et al. (2016) identified the barriers (e.g., lack of information, funding, and expertise) to multisector stakeholder collaboration and highlighted the importance of engaging academic stakeholders in flood risk governance through a case study of the flood-prone informal settlement of Sweet Home in Cape Town. 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) offered strategies for multisector stakeholder collaboration by exploring stakeholder values and how their value priorities changed across different phases of a disaster. Li et al. (2021) proposed a plan evaluation framework to identify various stakeholders' preferences for different disaster plans to improve the quality of resilience planning.

Previous studies have offered valuable contributions to multisector stakeholder collaboration in the disaster context. However, two main knowledge gaps remain unfilled. First, there is a lack of stakeholder collaboration literature that focuses on housing resilience planning or disaster mitigation. Existing studies (e.g., Kapucu 2014; Jiang and Ritchie 2017; Curnin and O'Hara 2019) emphasized the importance of multisector stakeholder collaboration in various disaster contexts, and most focused on disaster response and recovery phases. More attention should be paid to the mitigation phase, because it could reduce the long-term risks to human lives and properties due to natural hazards. Although some studies have focused on mitigation planning (e.g., Petak 2002; Mojtahedi and Oo 2017; Li et al. 2020), those studies did not focus on housing resilience planning in particular. Housing is a key component of a resilient city that allows people to cope with risks and disturbance (Porter et al. 2018). Building housing resilience has become a priority among governments because it can help protect lives from disasters and build resilient communities (TWB 2019; Gosain et al. 2022). Second, there is a lack of research that examines the current stakeholder collaboration mechanisms in housing resilience planning. Although many studies (e.g., Sitas et al. 2016; Pathak et al. 2020; Li et al. 2021) have proposed different approaches to facilitate multisector stakeholder collaboration in disaster contexts, those studies have not focused on studying how these stakeholders collaborate when dealing with resilience issues in practice. The involvement of various stakeholder sectors largely influences resilience planning processes. There also is a need to understand the roles, capabilities, influences, and/or interactions of different stakeholder sectors. Understanding stakeholder involvement and relationships in housing resilience planning is imperative because it may offer insight into and solutions for more-effective stakeholder collaboration.

Research Context and Methodology

GM&B is a low-lying but heavily developed coastal area located in the southeast of Florida. It includes Miami-Dade County, the City of Miami, and the City of Miami Beach. Compared with other regions or areas in the US, the GM&B region was selected for this study because this region has become increasingly vulnerable to multiple natural hazards (e.g., hurricanes, flooding, and sea-level rise) and social stresses and crises (e.g., social inequalities and affordability), which places the local housing market in an urgent need for resilience planning. This region provides an important case study for housing resilience planning, which may serve as a descriptive model illustrating how a major coastal region cooperates to mitigate future hazards.

Over the last several decades, the GM&B region has been severely impacted by several major disasters. For example, in 1992, Hurricane Andrew hit the GM&B region, leaving 175,000 people homeless. In 2005, two hurricanes—Hurricane Katrina and Hurricane Wilma—affected this region within a period of 1 month and caused $2.9 billion of damage, leaving many neighborhoods with no power for weeks (GM&B 2019). In 2017, Hurricane Irma caused a massive evacuation of local residents, and it took several months for clean-up and recovery. In addition, research shows that the sea level has risen by 4 in. since 1992, and an additional approximately 3–7 in. of sea-level rise is expected by 2030, which could cause serious erosion and damage to the already aging housing and infrastructure (GM&B 2019). Hanson et al. (2011) found that Miami is the top globally ranked city in terms of assets exposed to projected coastal flooding by 2070. In addition, many local housing stocks are old and not compliant with the current building codes. Approximately 86,519 residential structures in Miami-Dade County were built before 1990, and they are considered to be the most vulnerable to potential disasters such as hurricanes and flooding. With natural hazards becoming more frequent and damaging, the vulnerable housing in the GM&B region is at high risk (Murray and Zyryanova 2020).

In addition, the GM&B faces severe social stresses and crises in terms of housing affordability, which exacerbates the existing social inequalities and conflicts (Florida and Pedigo 2019). In 2019, the GM&B ranked as the seventh least-affordable large metropolitan area in the world, and about 6 of 10 employed residents were housing cost-burdened, meaning that these residents spent more than 30% of their incomes on housing (Florida and Pedigo 2019). Recent inflation in the consumer price index in the United States has dramatically worsened the problem in just the last year. For example, Redfin.com estimates that Miami home prices may increase 28% during the summer of 2022, and Realtor.com predicts that rent prices may increase 57.1% compared with the previous year (Redfin 2022; Xu and Hale 2022). The housing affordability crisis in this region has further exacerbated its high level of social inequality. As rents and housing prices continue to rise while incomes fail to keep pace, a disproportionate burden is placed on minorities and/or the economically disadvantaged, which worsens existing social inequalities and conflicts. Moreover, the mounting threats posed by climate change and sea-level rise will only exacerbate the region's housing affordability crisis over time (Florida and Pedigo 2019). Such a crisis affects the residents' lives and poses a major threat to the region's long-term social stability and economic prosperity (Florida and Pedigo 2019).

Ensuring a safe, decent, and affordable housing environment is a basic human necessity, and it has become an imperative policy priority in the GM&B region (Murray and Zyryanova 2020). Thus, there is an urgent need to facilitate housing resilience planning in response to potential challenges. The GM&B joined the

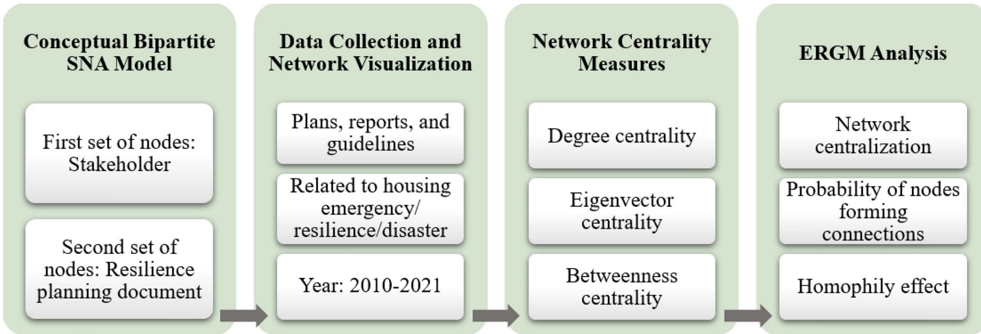

Fig. 1. Overview of methodology.

100 Resilient Cities in 2016, which was launched by the Rockefeller Foundation to improve the resilience of the cities around the world in response to various physical, social, and economic challenges in the 21st century (GM&B 2019).

In our research, a conceptual bipartite SNA model was built to represent the multisector stakeholder collaboration and engagement network on housing resilience planning. The relevant data then were collected to build the SNA model. The model was analyzed using two main methods: centrality measures that describe the positioning of the stakeholders in the network; and ERGM analysis that provides an inferential basis for estimating drivers of tie formation in the network. Network centrality measures use the graph theory to calculate the importance of nodes in the network, whereas ERGM infers drivers of network formation by explicitly modeling dependencies in tie formation using simulation techniques. Fig. 1 provides an overview of the methodology. The following sections describe the methodology in detail.

Conceptual Bipartite SNA Model

A bipartite SNA model was built to analyze the collaboration and involvement of multisector stakeholders in housing resilience planning. There are two sets of nodes in the proposed SNA model. One set of nodes represents the housing resilience planning documents, and the other set of nodes represents the stakeholders involved in developing these housing resilience planning documents. In this type of two-mode, or bipartite, network, a tie or connection exists only between a stakeholder and a planning document, to represent the stakeholder's contribution to the housing resilience planning document. This kind of social network is also known as an affiliation network in network science (Wasserman and Faust 1994). Compared with a one-mode network, a two-mode network can represent an affiliation network in an effective and visually observable manner.

Data Collection and Network Visualization

To collect the data for the proposed bipartite network, we systematically reviewed all the formal documents published on government websites, including the websites of all the offices or departments (e.g., Division of Emergency Management and Department of Housing and Community Development) of the City of Miami, the City of Miami Beach, and Miami-Dade County. Three major inclusion criteria were followed in the systematic review. First, the topics of the documents had to relate to "housing" and at least one topic among "emergency," "resilience," or "disaster," which ensured the contents of the selected documents were relevant. Second, the types of the documents had to be plans, reports, or guidelines, because these types of documents typically offer formal strategies for or guidance on housing resilience planning. Third, because we focused on analyzing housing resilience planning in recent years, the publication year of the documents was from 2010 to 2021. Using these inclusion criteria, a total of 39 documents were included in our analysis. The distribution of these documents based on the inclusion criteria is summarized in Table 1.

After collecting all the housing resilience planning documents, two sets of nodes of the SNA model were coded for analysis. To code the first set of nodes, all the titles of documents were extracted and abbreviated using acronyms for the titles. Based on the planning scope of the documents, they were classified into three levels: city level, county level, and regional level. To code the second set of nodes, the names of the stakeholders that contributed to each document were identified and abbreviated with unique acronyms. To be specific, the stakeholders were identified when their names were listed as authors, collaborators, and/or contributors in the resilience planning documents. Based on a comprehensive literature review of stakeholders in disasters (e.g., Mojtahedi and Oo 2017; Al-Fazari

Table 1. Distribution of documents by region, year of publication, and scope

Feature	Number of documents
Region	
City of Miami	12
City of Miami Beach	8
Miami-Dade County	17
City of Miami and Miami-Dade County	1
City of Miami, City of Miami Beach, and Miami-Dade County	1
Year of publication	
2021	1
2020	6
2019	9
2018	6
2017	6
2016	5
2015	3
2012	1
2011	1
2010	1
Scope	
Housing and resilience	2
Housing and emergency	5
Housing and disaster/emergency	9
Housing and resilience/emergency	7
Housing and resilience/disaster/emergency	16

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and Kasim 2019; Seifi et al. 2019; Pathak et al. 2020), the stakeholders were classified into five categories: public agencies, private industries, NGOs, academia, and community residents. A tie between the nodes occurred when a stakeholder made contributions to the planning document, creating a bipartite stakeholder-by-document network. Stakeholders therefore were connected indirectly (affiliated) to each other through the planning document. Thus, the ties represented the affiliation relationships between the stakeholders and the housing resilience planning documents. In this study, the analysis treated the bipartite network as an undirected (i.e., the edges do not have directionality) and binary (i.e., the edges are nonvalued) network. The network was generated from these data and visualized using Gephi version 0.9.1.

Network Centrality Measures

To answer Research question R1, three network centrality measures were used to describe the positions of the stakeholders in the network: degree centrality, eigenvector centrality, and betweenness centrality. Each centrality measure analyzes the social network from a unique perspective to show the importance of a given node. Degree centrality [Eq. (1)] counts the number of direct ties to which a focal node is connected (Newman 2008). It shows the "popularity" of a node (Freeman 1978; Newman 2008). In our network, degree centrality was measured to indicate the number of housing resilience documents to which each stakeholder contributed. The average degree centrality of each stakeholder sector was obtained by averaging the degree centralities of all stakeholders that belonged to that particular sector. A higher degree of centrality for a stakeholder sector implies that this stakeholder sector is more popular and contributes more to housing resilience planning

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

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

Compared with degree centrality, eigenvector centrality [Eq. (2)] further considers the influence of nodes to which a focal node is connected (Newman 2008). Eigenvector centrality acknowledges that a focal node is more influential when the neighboring nodes themselves are more influential (Newman 2008). In our network, the eigenvector centrality measures the importance of a stakeholder based on the importance of its adjacent nodes, which are the housing resilience planning documents. The average eigenvector centrality of each stakeholder sector was calculated by averaging the eigenvector centralities of the stakeholders that belonged to that particular sector. A higher average eigenvector centrality for a stakeholder sector indicates that this stakeholder sector is connected to those important planning documents (i.e., those planning documents with high eigenvector centralities themselves), thus making this stakeholder sector more important in the housing resilience planning processes

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

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

Betweenness centrality [Eq. (3)] is a network measure that accounts for the shortest path of the whole network (Freeman 1978). It measures how often a node lies on the shortest path between two other nodes (Freeman 1978). Nodes with higher betweenness centralities are considered to have higher influence or control over information flow. In our study, the betweenness centrality of each stakeholder was analyzed to measure how often a stakeholder was between two other nodes. The average betweenness centrality of each stakeholder sector then was obtained. A higher average betweenness centrality for a stakeholder sector indicates that this stakeholder sector has powerful control of information flow, thus making itself important in the whole network

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

where $C_b(i)$ = betweenness centrality of node i; g_{jk} = number of shortest paths between node j and node k; and $g_{jk}(i)$ = number of those paths that go through node i. The descriptive centrality measures were calculated using the igraph package version 1.2.6 in R version 3.6.1 (Csardi and Nepusz 2006).

To answer Research question R2, the Kruskal–Wallis H test was performed to assess whether there were significant differences in the network measures across different stakeholder sectors. The Kruskal–Wallis H test is a nonparametric test that typically is used for comparing the differences among three or more independent samples (Leard Statistics 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) then were performed to test which pairs of stakeholder groups were significantly different.

Exponential Random Graph Model

To answer Research questions R3 and R4, ERGM analysis was performed to analyze multisector stakeholder involvement in housing resilience planning processes. ERGM is a statistical inference model that is useful for modeling complex social networks. It aims to identify factors that influence the probability of a simulated network evolving with similar properties to the observed social network (Lusher et al. 2013). The traditional statistical methods, such as the logistic model, are based on the assumption of network tie independence, which is not suitable for SNA as SNA is intrinsically interdependent (Wasserman and Faust 1994). Although ERGMs have become quite common in the networks literature, ERGMs are less commonly used to analyze bipartite social networks (e.g., Hamilton et al. 2018; Mauldin et al. 2021; Lubell and Robbins 2022). The formation of ties in a social network is the result of many factors that interact. ERGM assumes that the network ties are interdependent, and it predicts the probability of tie formation between nodes (Lusher et al. 2013; Koskinen and Daraganova 2013). Endogenous structural effects such as reciprocity, popularity, and triad closure affect the tie formation, as in the human social network. Exogenous covariates, such as attributes of nodes or ties, also influence how a network tie is formed (Wang et al. 2009; Lusher et al. 2013). The general form of the ERGM is shown in Eq. (4) (Hunter et al. 2008). ERGM is estimated by Markov-chain Monte Carlo maximum-likelihood estimation (Hunter et al. 2008)

$$P(Y = y) = \frac{\exp(\theta' s(y))}{k(\theta)} \tag{4}$$

where Y = random variable for the state of the network (with realization y); $s(y)$ = vector of model statistics (including endogenous effects and exogenous covariates) for network y; θ = vector of coefficients for those statistics; and $k(\theta)$ = normalizing constant in the numerator that is summed over all possible networks.

In our ERGM analysis, the stakeholder was the first mode of the network, and the resilience planning document was the second mode of the network. Six ERGM terms were selected in our ERGM analysis: edge, gwb1degree, gwb2degree, b1factor, b2factor, and b1nodematch. Our analysis started with the simplest ERGM term, edges, which measured the total number of edges in the network. This term was used to control the overall density of the network. Then two endogenous structural terms, the geometrically weighted degree (GWD) distribution of the stakeholders (gwb1degree) and the GWD distribution of the housing resilience planning documents (gwb2degree) were studied. These two terms were based upon the structural configurations of the whole network. These terms model the distribution of degrees across all nodes in the network rather than measuring specific degree values (Hunter and Handcock 2006). The results of these two terms reflect the overall tendency of network dispersion; a negative coefficient indicates a strong centralization tendency, and a positive coefficient indicates a strong dispersion tendency in the network (Koskinen and Daraganova 2013). In our study, a negative result of gwb1degree indicates that the degree distribution of the network centers around a few stakeholders. Specifically, a few very active stakeholders contributed to many housing resilience planning documents, and the majority of stakeholders contributed to a few housing resilience planning documents. Similarly, a negative result of gwb2degree indicates that the degree distribution of the network centers around a few housing resilience planning documents—i.e., a few housing resilience documents had many stakeholders involved, and most housing resilience planning documents had a few stakeholders involved. When performing the analysis, the same decay value was used for both gwb1degree and gwb2degree. The decay value that was tested ranged from 0.1 to 0.9 in increments of 0.1. The model that generated the smallest Akaike information criterion (AIC) and Bayesian information criterion (BIC) was identified as the best model.

In addition to the structural terms, the exogenous covariates were explored to describe the influence of node attributes on network formation. Terms b1factor and b2factor were used to explore the number of times a node in one mode formed connections with nodes in the other mode. Specifically, b1factor explored the probability relationships among different stakeholder sectors (i.e., public, private, NGOs, academia, and community residents) when forming ties with the housing resilience planning documents. Term b2factor studied the probability relationships among different levels (e.g., city level, county level, and regional level) of housing resilience planning documents when forming ties with the stakeholders. In addition, b1nodemacth term was analyzed to test the homophily effect of the first mode (i.e., stakeholders). A positive result of b1nodemacth term indicates the existence of the homophily effect in the network, which means that two stakeholders within the same sector were more likely to form ties with the same housing resilience planning document.

The analysis of ERGM was conducted in R, using the statnet version 2019.6 software package (Hunter et al. 2008; Handcock et al. 2008). The ERGM was evaluated by comparing the network statistics drawn from the simulated networks with the observed network to describe how well the model fitted the observed network. The goodness-of-fit plots of the ERGM are shown in the Appendix. Overall, our ERGM converged and fitted well, which means the ERGM results are valid for further interpretation.

Results

Results of Network Visualization

The visualization of the bipartite SNA model is shown in Fig. 2. The circular nodes represent the collected housing resilience planning documents, and nodes of other shapes represent the stakeholders from different sectors. The size of each node is based on the degree centrality of the node. A total of 305 nodes and 476 ties were identified in the network, in which 266 nodes are stakeholders and 39 nodes are housing resilience planning documents. There are relatively larger numbers of stakeholders from public agencies, private industries, and NGOs: 81 public stakeholders (triangles), 80 private stakeholders (pentagons), and 90 NGO stakeholders (squares). In contrast, stakeholders from academia and community residents are relatively few: only 10 stakeholders from academia (hexagons) and 5 stakeholders from community residents (heptagons). Based on the sizes of the nodes (degree centrality), 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 contributed the most to housing resilience planning. Florida Power & Light and JPMorgan Chase & Co. are the most-engaged private stakeholders. Catalyst Miami, South Florida Community Development Coalition, and Miami Homes for All are the NGOs that were involved more in housing resilience planning. The academic stakeholders, such as the University of Miami, Florida International University, Miami Dade College, and the University of Florida, were found to have made more contributions to these planning documents. Except for the University of Florida, all these universities are located in South Florida.

Results of Network Centrality Measures

The results of network centrality measures, including average degree centrality, average eigenvector centrality, and average betweenness centrality of the five sectors of stakeholders, are shown in Figs. 3–5, respectively. The academic and public stakeholders had higher average degree centralities (3.100 and 2.580, respectively), followed by the NGOs (1.567) and the private industries (1.125) (Fig. 3). This indicates that academia and the public agencies have relatively higher numbers of ties or connections to these housing resilience planning documents. It implies that the stakeholders from academia and public agencies are more involved in resilience planning processes, which may make them more experienced and influential in the network. In contrast, the community residents had the lowest average degree centrality (1.000). This result shows that each community representative is likely to contribute to only one housing resilience planning document on average.

The stakeholders from public agencies had the highest average value (0.120) of eigenvector centrality (Fig. 4). The academic sector had a relatively higher average eigenvector centrality (0.095) as well, compared with those of the NGOs (0.033), private industries (0.018), and community residents (0.009). This implies that the stakeholders from public agencies and academia are more likely to contribute to those important housing resilience planning documents (i.e., documents with high eigenvector centralities). Thus they are considered to be the most influential and important sectors in housing resilience planning processes. In contrast, the community resident sector had the lowest average eigenvector centrality, indicating they made limited contributions to the important housing resilience planning documents.

There were large variations in the average betweenness centralities among the five sectors of stakeholders, and academic stakeholders had the highest betweenness centrality (695.130) among

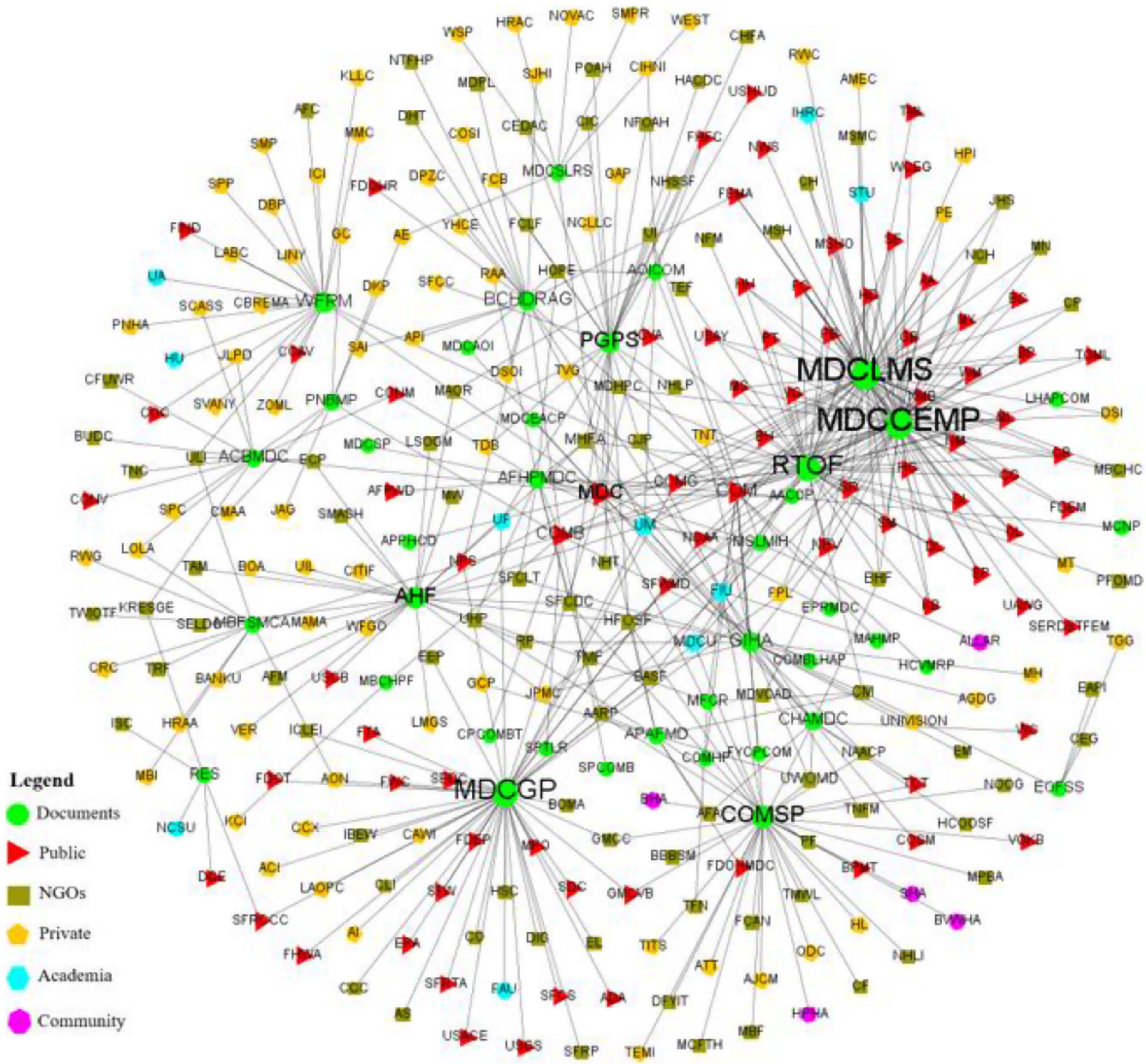

Fig. 2. Bipartite network visualization.

all the sectors (Fig. 5). This indicates that the academic stakeholders have the highest control power of bridging information flows in the network and preventing network fragmentation. The stakeholders from public agencies had a relatively higher value (387.471) as well. These results reinforce the findings that the academic and public stakeholders are the most influential sectors in housing resilience planning processes because they control the information exchange across different sectors. In contrast, the average betweenness centralities for the NGOs, private industries, and community residents were much lower (68.820, 13.984, and 0, respectively). The zero result of average betweenness centrality for the community resident sector indicates that the community residents have no control power over information exchange, which further demonstrates their least-influential role in planning processes.

After computing the network centrality measures of all stakeholder sectors, Kruskal–Wallis H tests were performed to determine if there were significant differences among these stakeholder sectors in each centrality measure. The p-values for the three network centrality measures all were less than 0.05, which indicates that there were significant differences in the centrality measures among different stakeholder sectors. Post hoc pairwise comparisons were conducted to test which pairs of sectors were significantly different. Table 2 summarizes the results of the post hoc pairwise comparisons. The p-values had similar patterns in the three network measures (Table 2). There were significant differences between five pairs of stakeholder sectors: public and private stakeholders, public stakeholders and NGOs, public stakeholders and community residents, private stakeholders and NGOs, and private and academic stakeholders.

Results of Exponential Random Graph Model Analysis

The results of the ERGM analysis are summarized in Table 3. The estimation result of the ERGM term gwb1degree was positive

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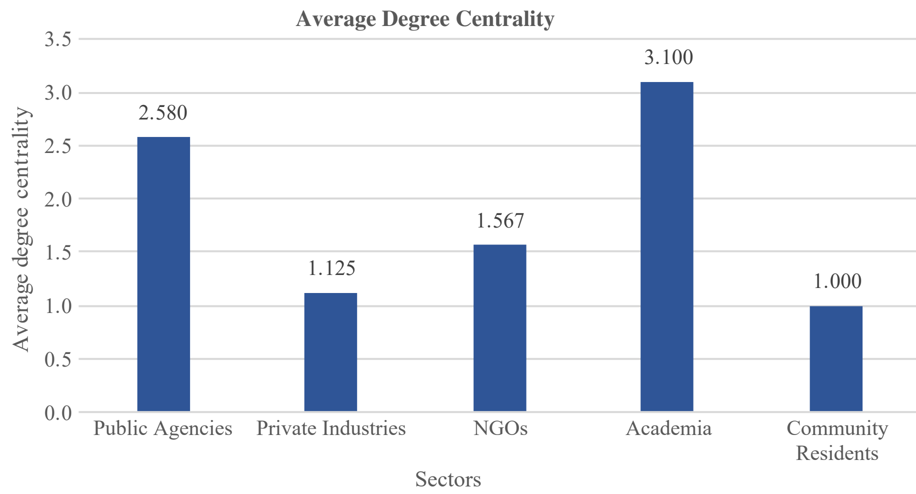

Fig. 3. Results of average degree centralities by stakeholder sector.

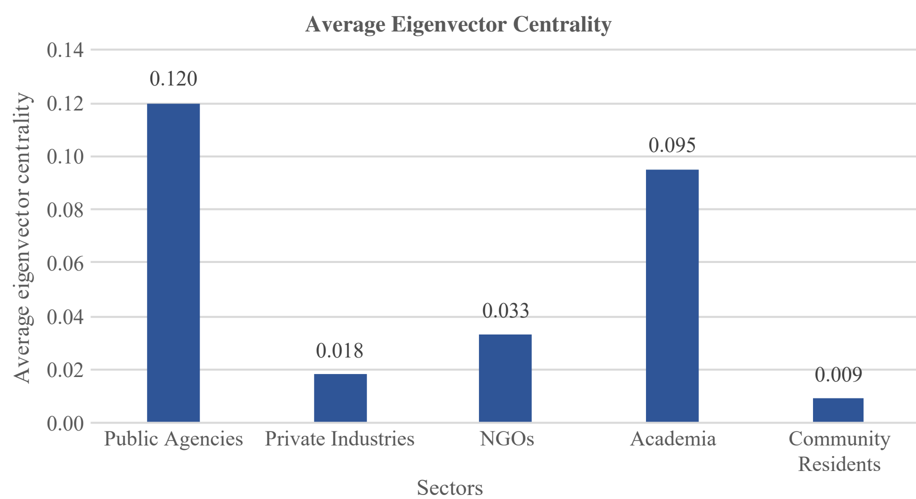

Fig. 4. Results of average eigenvector centralities by stakeholder sector.

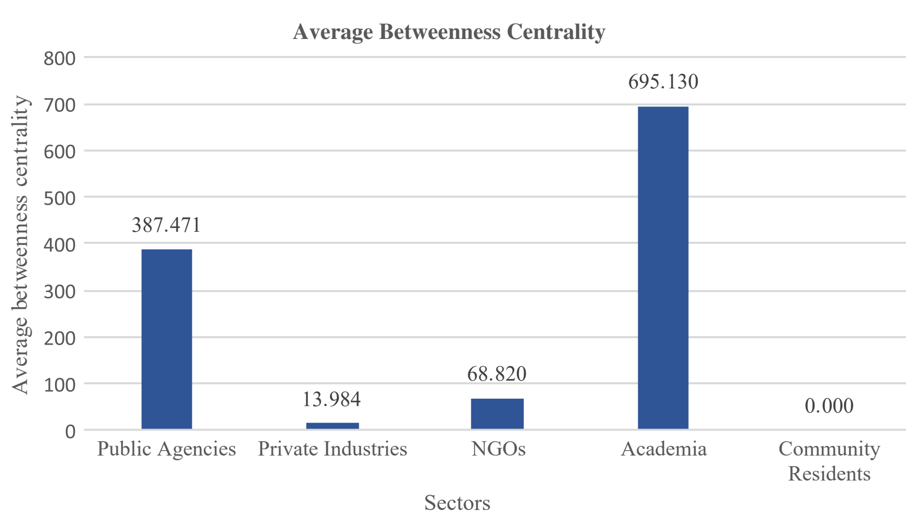

Fig. 5. Results of average betweenness centralities by stakeholder sector.

Table 2. Results of post hoc pairwise comparisons

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

Note: S1 = public agencies; S2 = private industries; S3 = NGOs; S4 = academia; and S5 = community residents.
[a]p-value is significant at 0.05 level.

Table 3. Results of ERGM analysis

Network characteristics	Estimate	Standard error	p-value
Edges	−3.864	0.118	$<1\times10^{-4}$[a]
gwb1degree.fixed.0.2	3.745	0.501	$<1\times10^{-4}$[a]
gwb2degree.fixed.0.2	−3.970	0.692	$<1\times10^{-4}$[a]
b1factor.Type.NGOs	−0.773	0.157	$<1\times10^{-4}$[a]
b1factor.Type.Private	−1.706	0.284	$<1\times10^{-4}$[a]
b1factor.Type.Community	−2.004	0.921	0.0295[a]
b1factor.Type.Academia	0.921	0.241	0.0001[a]
b2factor.Type.County level	0.556	0.105	$<1\times10^{-4}$[a]
b2factor.Type.Regional level	0.557	0.113	$<1\times10^{-4}$[a]
b1nodematch.Sector type	0.075	0.002	$<1\times10^{-4}$[a]

Note: The stakeholder is the first mode, and the housing resilience planning document is the second mode.
[a]p-value is significant at 0.05 level.

(3.745) and significant ($p<1\times10^{-4}$). This result indicates that this network is not a stakeholder-centered network, and there is no preferential attachment effect identified among the stakeholders. The result of gwb2degree was negative (−3.970) and significant ($p<1\times10^{-4}$). This indicates that this bipartite network is a document-centered network, and there are high variations in the number of stakeholders who are involved in housing resilience planning documents. This implies that the ties tend to concentrate on a few resilience planning documents, and those documents have preferential attachments. In other words, a few housing resilience planning documents have many stakeholders involved, and most housing resilience planning documents have only a few stakeholders involved.

Term b1factor explored the probability of each stakeholder sector forming connections with housing resilience planning documents. In this analysis, the public agency was used as the reference group. The b1factor coefficients for the NGOs, private industries, academia, and community residents were −0.773, −1.706, −2.004, and 0.921, respectively (Table 3). The results of b1factor all were significant, with p-values lower than 0.05. These results indicate that, when other network properties remain the same, the probability of the public agencies forming a tie with housing resilience planning documents is 2.166 [exp (0.773)] times that of the NGOs, 5.505 [exp (1.706)] times that of the private industries, and 7.421 [exp (2.004)] times that of the community residents, and the probability of the academic sector forming a tie with housing resilience planning documents is 2.512 [exp (0.921)] times that of the public agencies. These results further reinforce the findings from centrality measure analysis that the academic and public stakeholders are more likely to contribute to housing resilience planning processes.

Analysis of b2factor focused on analyzing the probability of each type of planning document when forming connections with stakeholder sectors. In this analysis, the city-level planning document was used as the reference group. The b2factor coefficients for the county-level and regional-level were 0.556 and 0.557, respectively (Table 3). The results suggest that the probability of the county-level housing resilience planning documents forming a tie with a stakeholder is 1.743 [exp (0.556)] times that of the city-level documents, and the probability of the regional-level housing resilience planning documents forming a tie with a stakeholder is 1.745 [exp (0.557)] times that of the city-level documents.

Term b1nodematch examines the homophily effect of the stakeholder sector. The result was positive (0.075) and significant ($<1\times10^{-4}$), which means that the stakeholders within the same sector are more likely to contribute to the same housing resilience planning documents together (Table 3).

Discussion

Contributions of Multisector Stakeholders

The results of network centrality measures and ERGM consistently indicate that, compared with sectors such as NGOs, private industries, and community residents, public agencies contribute more to housing resilience planning processes. This finding coincides with those of other studies in the disaster domain (e.g., Li et al. 2020) that identified public agencies as the most critical sector in resilience planning processes. This may be due to the fact that public agencies share a stronger sense of public responsibility for improving disaster resilience within communities (Raikes et al. 2019). Such a sense of responsibility may come partially from legal or policy requirements (e.g., the Robert T. Stafford Disaster Relief and Emergency Assistance Act and Presidential Policy Directive/PPD-8) that explicitly indicate the roles and responsibilities of different divisions and sectors within public agencies. It also may be because political leaders personally have the responsibility to increase the resilience of cities with the goal of bringing benefits to local communities and their own political futures (Valero et al. 2015; Crosweller and Tschakert 2021). In addition, public agencies typically have a higher capability of coordinating various resources (e.g., knowledge resources, human resources, and material resources) in resilience planning processes. They also may possess strong leadership and organized structures that allow them to unite stakeholders from different backgrounds to maintain collaboration relationships in resilience planning. Moreover, public agencies play a vital role in providing sufficient resources (e.g., financial support, emergency response services, and evacuation shelters) to support resilience planning and/or ensure effective policy implementation (Kusumasari et al. 2010).

Similar to public stakeholders, academic stakeholders also play a critical role in developing housing resilience plans, as per our results of network measures and ERGM analysis. The active participation of academic stakeholders indicates that there is a positive collaborative environment for policy decision-making that incorporates multiple epistemic perspectives toward solving complex public problems (Raadschelders and Whetsell 2018). The continuing potential disasters require scientific knowledge production and policy actions to reduce disaster risks (Weichselgartner and Pigeon 2015). Academic stakeholders offer their professional knowledge and research expertise that support disaster resilience. They are capable of offering scientific evidence and measurable outcomes regarding resilience planning, thus ensuring that knowledge-driven policies are being made. Having academic stakeholders play influential roles in a network allows all sectors to benefit from relevant knowledge, expertise, and state-of-art innovations (e.g., high-tech products and new methods). Thus, it maximizes the use of knowledge and transfers them into policy practices (Abedin and Shaw 2015; Izumi et al. 2019). Moreover, academic stakeholders are able to provide education and training to the public throughout resilience planning processes, which raises public awareness and allows the public to better respond to disasters (Seifi et al. 2019).

Our study found that the involvement of community residents in housing resilience planning processes is relatively low compared with that of all other sectors. After further investigating the contents of the housing resilience planning documents, we found that community residents typically are not acknowledged formally as contributing to the plans, and the discussion about their contribution and involvement usually is vague. Furthermore, we found that the limited number of community organizations that were represented were dominated almost entirely by homeowner associations, which represent only property owners, and do not represent renters or the homeless. This seems to imply that a large segment of community residents does not have much opportunity to participate in resilience planning and their voices were not quite heard. Although community engagement may be a time- and effort-consuming process, it is crucial to the success of housing resilience planning. Community residents are those who are impacted by the resilience initiatives, and their thoughts and opinions reflect what users value and need. Although there are many barriers (e.g., limited financial resources, cultural diversity, and lack of trust in government) that may impede community engagement (Gamboa-Maldonado et al. 2012; Geekiyanage et al. 2020), systemically involving community residents remains imperative. Such engagement allows community residents to openly express and discuss their values and needs, which makes resilience initiatives more satisfactory and user-driven (Lassa 2018). It also could empower community residents to be more informed and supportive of resilience initiatives or investments, which eventually will lead to smoother and more-effective policy implementation.

More-Balanced Collaboration Mechanisms Needed

This study found that various sectors of stakeholders have significantly different levels of involvement or influence in housing residence planning. This result suggests that more-balanced collaboration mechanisms are needed in this process. Although it is expected that different stakeholder sectors may have varying levels of involvement, an ideal collaboration network would allow for more-balanced contributions in which different sectors of stakeholders share some similar levels of involvement, influence, and/or power of controlling information flows. Existing studies (e.g., Abedin and Shaw 2015; Sharifi and Yamagata 2018; Lassa 2018; Seifi et al. 2019) emphasized the importance of involving different stakeholder sectors in resilience planning. A more-balanced collaboration mechanism will allow stakeholders from different backgrounds to better express their unique needs, concerns, and values, which could enhance multisector stakeholder collaboration. Through a more-balanced collaboration mechanism in resilience planning, the knowledge and needs of various stakeholders can be better integrated into decision-making processes, which could allow for more-appropriate distribution of resources, thus facilitating social equality (in terms of service, goods, and opportunities) in resilience planning (Matin et al. 2018; Meerow et al. 2019). In addition, a more-balanced collaboration mechanism shows equal respect to different stakeholder sectors, and it could lead to better relationships and enhanced trust among different stakeholders, which is necessary for effective housing resilience planning (Meerow et al. 2019).

Decentralized Collaboration Systems Needed

This study found that there are different levels of stakeholder engagement in various housing resilience planning processes. The results from ERGM analysis (i.e., gwb2degree) show that the majority of the plans have a few stakeholders involved, and only a few housing resilience plans have many stakeholders involved. This implies that the majority of stakeholder collaboration mechanisms for resilience planning are centralized, in which a few major or central stakeholders dominate decision-making processes. Despite the advantages of centralized collaboration such as high efficiency in decision-making, centralized collaboration has been criticized for not being effective in solving complex problems that require multidisciplinary knowledge (Ernstson et al. 2008; Luthe et al. 2012; Rijke et al. 2012). Resilience planning is a complex social issue that requires active participation and collaboration of various stakeholders (Marana et al. 2018; Ganji et al. 2019; Gosain et al. 2022), which makes the centralized collaboration mechanism unsuitable. Centralized collaboration may fail to integrate the needs, values, and views of the peripheral stakeholders into resilience planning processes. Our finding suggests that a decentralized collaboration mechanism is needed, through which both central and peripheral stakeholders can be involved in decision-making processes. The task of resilience planning could be distributed across various stakeholders through a decentralized collaboration mechanism. Decentralized collaboration is suitable for addressing complex problems because it offers more opportunities to engage various stakeholders and facilitates social learning and collaborative leadership (e.g., Bodin et al. 2006; Bodin and Crona 2009; Rijke et al. 2012; Mojtahedi and Oo 2017; Sharifi and Yamagata 2018), which is critical to facilitate efficient, equitable, and integrated development of housing resilience plans.

Intrasector Collaboration and Intersector Collaboration

The results of ERGM analysis (i.e., b1nodematch) show the existence of the homophily effect in housing resilience planning processes, in which stakeholders within the same sector are more likely to collaborate with each other. This indicates that intrasector collaboration currently is the dominating form of collaboration in housing resilience planning. Collaborative relationships often are based on trust and commitment to ultimate goals (Mandell and Keast 2007). Stakeholders from the same sector often share similar values and normally have a higher level of trust in each other, and thus they naturally have a higher tendency to collaborate with each other. Intrasector collaboration effectively facilitates internal information exchange and is more likely to remain a stable collaboration relationship. However, when addressing complicated issues that require knowledge and experiences from different areas, varying resources offered by different stakeholder sectors could become precious assets (Becker and Smith 2017). Many studies (e.g., Woodruff and Regan 2019; Li et al. 2020; Gosain et al. 2022) emphasized that it is important to facilitate intersector stakeholder collaboration. Such collaboration could pool resources together and greatly enhance social learning among multiple stakeholders such that stakeholders with different backgrounds can communicate and benefit from each other (Keen et al. 2005; Dow et al. 2013). It eventually will support more-robust and comprehensive housing resilience planning that benefits the entire community.

Conclusions, Contributions, and Future Work

Resilience planning requires effective collaboration and involvement of multisector stakeholders. By collecting data from the plans, reports, and guidelines in the GM&B region, this study built a bipartite SNA model to represent stakeholder collaboration and involvement in housing resilience planning. The results show that there are significant differences in the network measures (including average degree centrality, average eigenvector centrality, and average betweenness centrality) across the public agencies, private industries, NGOs, academia, and community residents. The results of network measures show that the public and academic stakeholders contributed more to housing resilience planning, whereas the involvement of the community residents was relatively low compared with that of all other sectors. The results of ERGM analysis further demonstrated that the public and academic stakeholders are more likely to contribute to housing resilience planning, whereas the community residents are the least likely to be involved in such processes. In addition, the results from the ERGM analysis show that the majority of housing resilience planning documents have only a few stakeholders involved, which suggests that the centralized collaboration mechanism is more dominant, and a decentralized collaboration mechanism may be needed in housing resilience planning. The ERGM analysis also shows that intrasector collaboration is more likely to happen because the stakeholders within the same sector tend to contribute to housing resilience planning together.

From a theoretical perspective, this research contributes to the body of knowledge in the disaster domain by providing a better understanding of stakeholder collaboration and engagement in housing resilience planning using bipartite SNA. By applying the network centrality measures and ERGM analysis, this study offers a quantitative assessment of the level of contributions and influences across five sectors of stakeholders (i.e., public agencies, private industries, NGOs, academia, and community residents) in housing resilience planning processes in the context of the GM&B region. Although different regions may have different circumstances (e.g., population, socioeconomic status, housing condition, geographic condition, types of hazards to which they are exposed) and their stakeholder collaboration and engagement mechanisms for housing resilience planning may vary, the analysis methods used in this study are applicable to other research regions to examine and/or offer a better understanding of stakeholder collaboration and engagement in resilience planning.

From a practical perspective, the findings of this study (e.g., more-balanced, decentralized, and intersector stakeholder collaborations are needed) offer important insight into better informing current practices of stakeholder collaboration and engagement in resilience planning. It has the potential to facilitate more-effective multisector stakeholder collaboration in responding to resilience challenges by informing decision makers about the pros and cons of current stakeholder relationships as well as challenges and opportunities for future collaboration. Based on the findings, some recommendations are offered to improve current practices. First, multisector stakeholder collaboration requires the engagement of various stakeholder sectors with more-balanced contributions. The level and quality of contributions from each sector should be assessed to ensure improved equity. In particular, the voices of traditionally less-involved stakeholders (e.g., community residents) need to be heard and accounted for in policymaking, which builds connections and trust among the stakeholders and promotes the effectiveness of policy implementation. Second, decision makers may work to build effective platforms (e.g., Ansell and Gash 2018) for better communication with various stakeholder sectors, especially the marginalized stakeholders. The engagement methods (e.g., public workshops, virtual meetings, and/or online surveys) should be tailored to each stakeholder sector to attract the marginalized stakeholders and facilitate participation. A database that includes the stakeholders' contact information and previous participation or experience in resilience planning may be developed to identify marginalized stakeholders and to support more-effective coordination and management of stakeholder networks. Third, to facilitate intersector stakeholder collaboration, training can be provided to various stakeholder sectors about how to become involved in resilience planning and how to improve their collaboration with others. It is vital for stakeholders to know

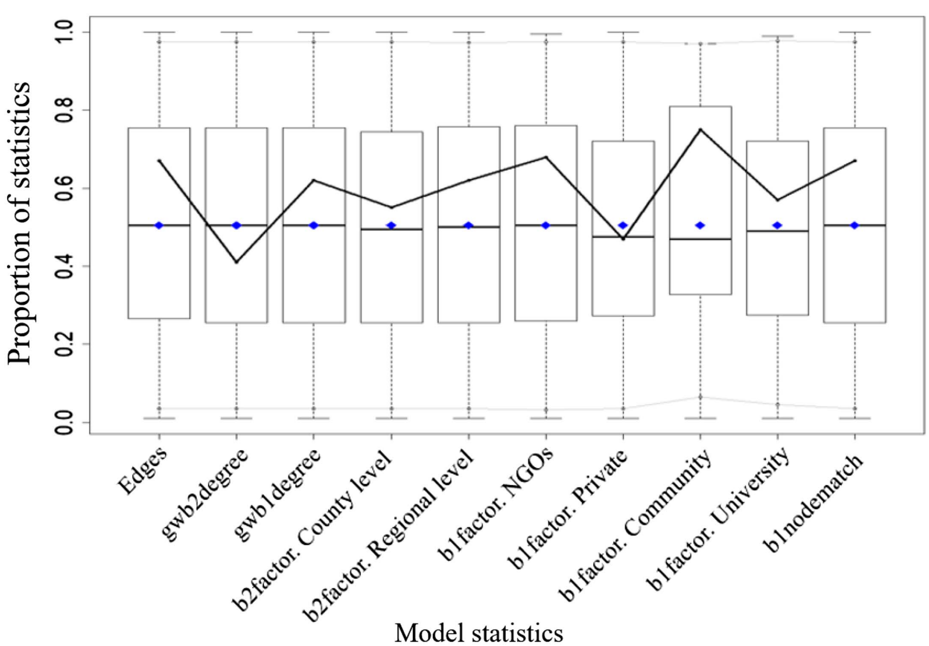

Fig. 6. ERGM goodness-of-fit assessment of model statistics.

their unique roles and responsibilities in resilience planning as well as the importance of working across sectors. Intersector stakeholder collaboration is more effective when the engagement process and motivations (e.g., issues, purposes, and benefits) of resilience planning are conveyed clearly to the stakeholders. In addition, there is a need to provide resources (e.g., funding) to encourage collaboration across sectors and address the bureaucratic barriers or procedures that may impede or complicate the process of intersector stakeholder collaboration.

The SNA model built in this study was based on the data collected from the planning documents. It is possible that certain stakeholders' contributions were not stated and acknowledged in these documents. In their ongoing and future research, the authors will collect other types of data using other data collection methods, such as surveys, which will allow first-hand data to be collected from the stakeholders directly. Other potential factors (e.g., demographic and socioeconomic backgrounds) that may impact the collaboration and engagement of stakeholders in housing resilience planning also warrant further investigation. In addition, the authors will focus on expanding the scope of the study to explore multisector stakeholder network structures in other relevant regions to better understand and/or compare the regional networks in order to correlate stakeholder network structures to housing resiliency outcomes. Such comparisons may offer more knowledge about and insight into what types and mechanisms of collaboration are needed to facilitate better resiliency outcomes.

Appendix. ERGM Goodness-of-Fit Assessment

Figs. 6–9 show the goodness of fit of the ERGM. Fig. 6 shows the goodness-of-fit diagnostic of model statistics. Fig. 7 shows the

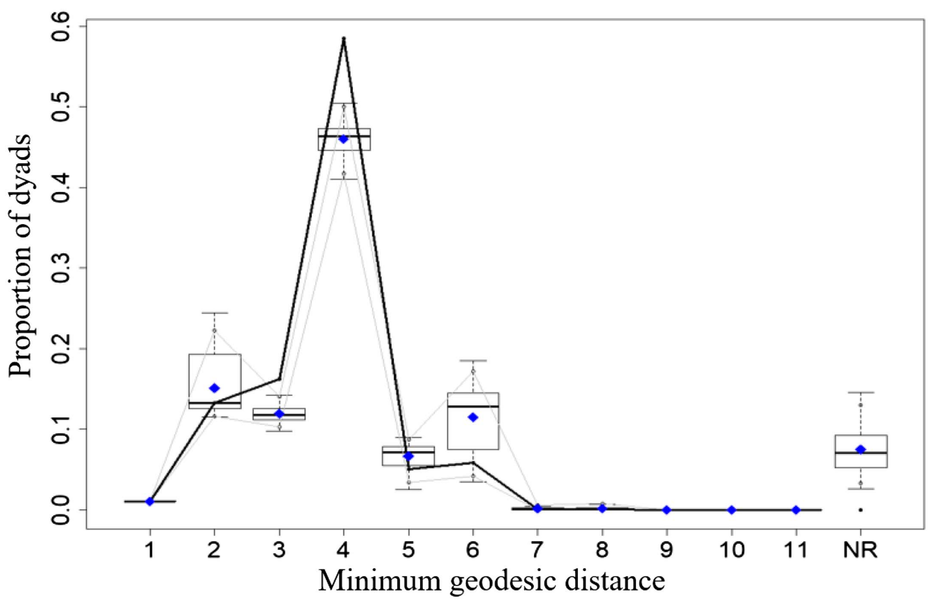

Fig. 7. ERGM goodness-of-fit assessment of minimum geodesic distance.

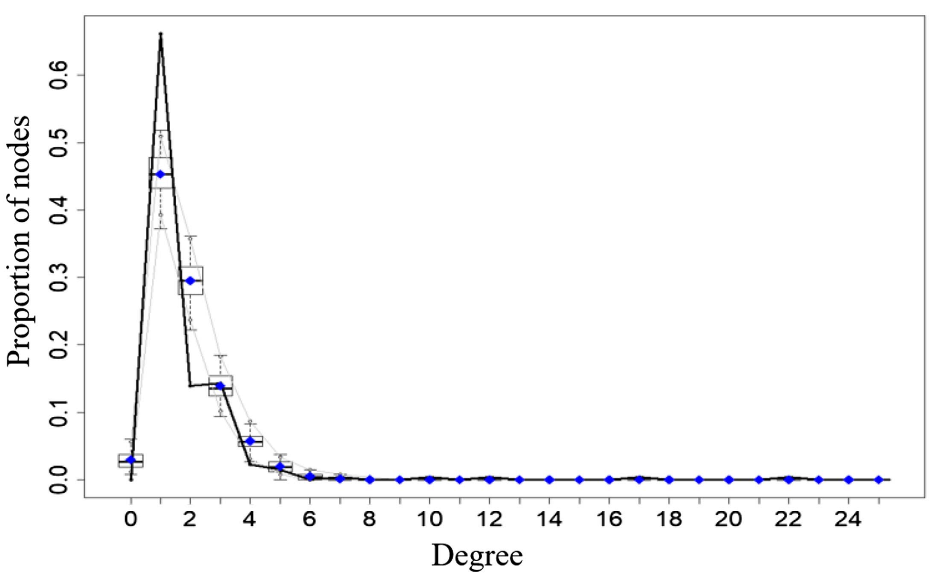

Fig. 8. ERGM goodness-of-fit assessment of degree distribution.

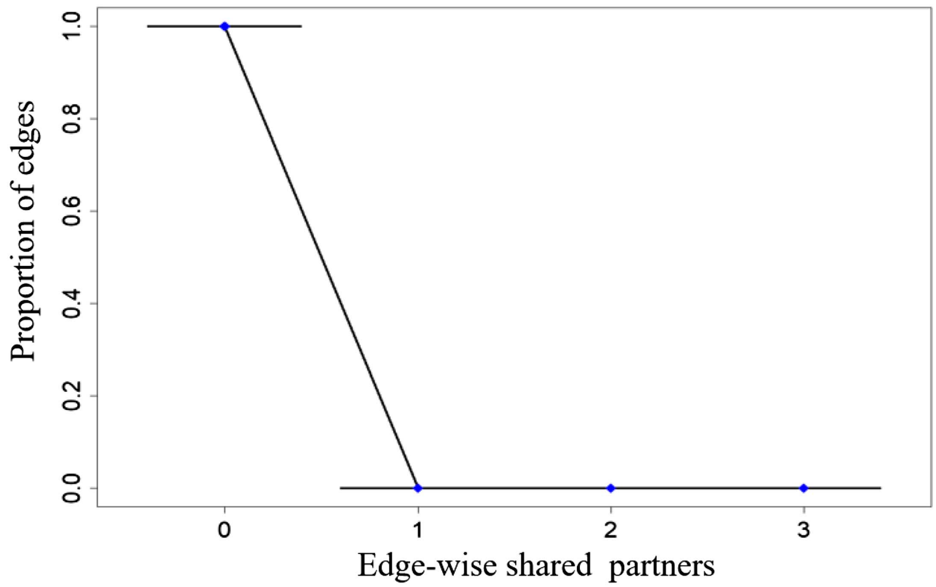

Fig. 9. ERGM goodness-of-fit assessment of edgewise shared partners.

goodness-of-fit diagnostic of minimum geodesic distance. Fig. 8 shows the goodness-of-fit diagnostic of degree distribution. Fig. 9 shows the goodness-of-fit diagnostic of edgewise shared partners. The boxplots represent the statistics drawn from simulated networks, and the thick black lines indicate the statistics of the observed network.

Data Availability Statement

Some data, models, or code that support the findings of this study are available from the corresponding author (Lu Zhang) upon reasonable request. These data or code include the data and the code used for building the networks.

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