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Local interactions and homophily effects in actor collaboration networks for urban resilience governance

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Abstract

Understanding actor collaboration networks and their evolution is essential to promoting collective action in resilience planning and management of interdependent infrastructure systems. Local interactions and choice homophily are two important network evolution mechanisms. Network motifs encode the information of network formation, configuration, and the local structure. Homophily effects, on the other hand, capture whether the network configurations have significant correlations with node properties. The objective of this paper is to explore the extent to which local interactions and homophily effects influence actor collaboration in resilience planning and management of interdependent infrastructure systems. We mapped bipartite actor collaboration network based on a post-Hurricane Harvey stakeholder survey that revealed actor collaborations for hazard mitigation. We examined seven bipartite network motifs for the mapped collaboration network and compared the mapped network to simulated random models with same degree distributions. Then we examined whether the network configurations had significant statistics for node properties using exponential random graph models. The results provide insights about the two mechanisms—local interactions and homophily effect—influencing the formation of actor collaboration in resilience planning and management of interdependent urban systems. The findings have implications for improving network cohesion and actor collaborations from diverse urban sectors.

Keywords: Policy preferences, Organizational proximity, Actor collaboration networks, Hazard mitigation, Network motifs, Exponential random graph models

Introduction

Collaboration among diverse actors is critical for effective resilience planning and management of interdependent infrastructure systems (IISs) (Li et al. 2019, 2021). In the context of this study, resilience is defined as “the capacity of human and infrastructure systems to prepare and plan for, absorb, recover from, or more successfully adapt to actual or potential adverse events (National Research Council 2012).” This definition highlights the importance of human systems affecting urban resilience that involve actors from diverse urban sectors (e.g., transportation, emergency response, environmental conservation, and flood control) with diverse priorities, resources, and responsibilities.

For example, actors from transportation sectors would focus on the improvement of roadway networks, while actors from flood control and environmental conservation may focus on flood mitigation and natural resource preservation. Urban resilience improvement is a collective action problem, and therefore needs to account for complex interactions and collaboration among diverse actors (Norris et al. 2008). Existing studies highlight the importance of actor collaboration for planning (Godschalk 2003; Woodruff 2018), emergency response (Chen and Ji 2021; Eisenberg et al. 2020; Kapucu 2005; Li and Ji 2021), and recovery (Aldrich 2011; Berke et al. 1993; Gajewski et al. 2011; Rajput et al. 2020) before, during and after urban disruptions. In the context of resilience planning and management of IISs, inadequate collaboration and coordination among diverse actors in the planning process exacerbates a lack of institutional connectedness (Dong et al. 2020) and would lead to contradictions and inconsistencies among networks of plans (e.g., land use, hazard mitigation, and environmental conservation) and increase social and physical vulnerabilities to urban disruptions (Berke et al. 2015, 2019; Malecha et al. 2018). For example, inconsistencies among land use approaches and hazard mitigation plans would allow urban growth in hazard-prone areas (Godschalk 2003).

Existing studies related to disaster management and environmental governance have explored factors that form the collaboration and social ties among diverse actors (Kapucu and Van Wart 2006; Nohrstedt and Bodin 2019). There is empirical evidence that actors with cognitive, organizational, and geographical proximity tend to form collaborations and social ties in inter-organizational networks (Balland 2012; Broekel and Hartog 2013). Matinheikki et al. (2016, 2017) found that actors with shared values tend to establish collaborations in a construction project. Hamilton et al. (2018) found that actors tend to engage in within-level (e.g., regional, local, and state) linkages in environmental governance compared with cross-level linkages. Studies regarding social network analysis demonstrated homophily phenomenon that implies actors with similar attributes tend to establish ties with each other (Gerber et al. 2013; Kossinets and Watts 2009; Shalizi and Thomas 2011). On the other hand, the heterophily phenomenon also exists; studies have shown that actors with dissimilar attributes tend to form social ties (Baranco et al. 2019; Kimura and Hayakawa 2008; Lozares et al. 2014; Rivera et al. 2010). The theory of structural holes in social networks suggests that actors seeking to advance their positions and to broaden their influence tend to form ties with those with different resources and skills (Burt 2004; Lazega and Burt 1995). McAllister et al. (2015) also argued that the links in networks related to urban governance were shaped based on the choices that actors make either to increase bonding capital, to reinforce shared norms and trusts, or to increase bridging capitals, linking with exotic resources. Asikainen et al. (2020) found that triadic closure (i.e., a structural property representing ties among three actors) and choice homophily are two important mechanisms for the evolution of social networks (e.g., communication networks), and that these two mechanisms are dependent upon each other. Although multiple existing studies explored the mechanisms that form the collaboration and social ties in different fields, such as organizational teams, very few studies investigated the drivers for collaboration in actor collaboration networks for resilience planning and management of IISs. Also, most collective action studies in the context of disaster management and environmental governance focus primarily on the structural properties of actors' social networks and have paid limited

attention to local interactions (based on examining motifs as topological signatures) and homophily effect (based on assessment of actor node attributes). The examination of these two mechanisms is essential for understanding and improving essential coordination in actors' networks for resilience planning and management of IISs.

In this study, therefore, our goal is to examine two important mechanisms for actor collaborations: local interactions and homophily effects in resilience planning and management of IISs. In this paper, we define local interactions as the stakeholder interactions on a small scale which can be examined by subgraphs or motifs in complex networks (Asikainen et al. 2020; Robins and Alexander 2004; Vázquez et al. 2004). We mapped actor collaboration networks for hazard mitigation before Hurricane Harvey based on a stakeholder survey administered in Harris County, Texas. The stakeholder survey captured collaboration among actors in various urban sectors (e.g., transportation, emergency response, flood control, environmental conservation, and community development) involved in hazard mitigation efforts. Also, the survey examined preferences of actors towards different types of flood risk reduction policies (e.g., land use approach, monetary policy, and engineering policies). Based on the mapped collaboration networks, we adopted network motif analysis and exponential random graph models (ERGMs) to examine the drivers for actor collaboration formation. We elaborate on the network motif analysis and ERGMs in the following sections.

Study context and data collection

During Hurricane Harvey, a Category 4 hurricane that made landfall on the Texas Gulf Coast in 2017, flooding due to release of water from Addicks and Barker reservoirs inflicted property and infrastructure damage in Harris County totalling 125 billion, particular in the Houston area. The release of water was necessitated to avoid even more severe damage if the impounded water would have breached the dams (NOAA & NHC 2018). Houston is a flood-prone city: Hurricane Harvey is only one in the long history of hurricane events in the Houston area. From 1935 to 2017, ten major flooding events occurred in the Houston area. Just before Hurricane Harvey, Memorial Day Floods in 2015 and Tax Day Floods in 2016 wreaked havoc in Houston, and caused 16 casualties and more than \$1 billion in losses (Berke 2019).

After Hurricane Harvey, we administered a stakeholder survey that focused on the Harris County area in Texas. The intent of the survey was to collect, among other things, essential data regarding actor collaboration for hazard mitigation and resilience planning of IISs, as well as actor preferences to different flood risk reduction policies. To map the actor collaboration network, we identified 95 influential actors involved in resilience planning from different urban sectors, including community development (CD), flood control (FC), transportation (TT), environmental conservation (EC), and emergency response (ER). These actors were listed in the survey roster as the actors that the survey respondents may have collaborated with. The survey question we asked the respondents to collect the collaboration data is included in the supplementary material.

Furthermore, we developed flood risk reduction policy actions to investigate preferences of actors from different urban sectors. The developed risk reduction policy actions included land use policies, engineering policies, and monetary policies. We identified these policies based on the strategies for urban flood resilience improvement discussed

in existing literature (Berke and Smith 2009; Brody et al. 2013, 2009; Burby 1998; Burby et al. 1999; Godschalk 2003). Table 1 lists the policy actions in the survey. Please see the supplementary material for survey questions to identify respondents' preferences to the developed policy actions.

On January 31, 2018, we conducted a pilot test of the stakeholder survey to collect feedback on the first-round survey instrument. For the pilot test, we randomly selected a group of 15 individuals from an initial list of selected organizations. We identified an initial list of organizations from different urban sectors, such as Harris County Flood Control District, City of Houston Floodplain Management Office, Texas Department of Transportation, Urban Land Institute, and The Nature Conservancy. We then used a snowball sampling method to expand the initial list by asking respondents to recommend relevant individuals and organizations to participate in the survey. Four respondents completed the pilot test, concluded on February 12, 2018. We refined the survey instrument based on the feedback received in the pilot test. The stakeholder survey was officially launched on February 15, 2018 and closed on April 10, 2018. We sent out a total of 795 invitations in 25 waves. We selected organizations involved in resilience planning from different urban sectors, both within and outside government, and at different scales (e.g., local, county, regional and state). We selected respondents within organizations that were in positions of management and planning and thus were informed about planning and were influential in their organizations. Finally, 198 individual respondents, representing 160 different departments of 109 organizations, (approximately 30% response rate) completed the survey.

Network models

We mapped the collaboration among diverse actors involved in hazard mitigation and resilience planning of IISs based on the survey results. We also mapped actor collaboration networks at different collaboration frequency levels, such as daily and weekly collaboration networks. The mapped networks are bipartite networks with two node sets: one comprises actors in the survey roster; the other, survey respondents. The edges in the mapped network represent collaborations among the actors for hazard mitigation and resilience planning of IISs. Figure 1 illustrates the way to map the

Table 1 Flood risk reduction policy actions in the survey

Policy description	Policy description
P1: limit new development in flood-prone areas	P9: protect wetland and open space
P2: elevate buildings	P10: improve stormwater systems
P3: strengthen infrastructure design standards	P11: build additional flood water drainage systems
P4: establish and implement infrastructure resilience program	P12: temporarily prohibit development in the period immediately after a disaster event
P5: minimize additional impervious surfaces, such as parking lots	P13: charge impacts fees for development in flood-prone areas
P6: build additional protective dams	P14: limit the development of public facilities and infrastructure in flood-prone areas
P7: build additional protective levees	P15: limit rebuilding in frequently flooding areas
P8: build more catchment reservoirs and retention ponds	P16: buyout or otherwise acquire damaged property

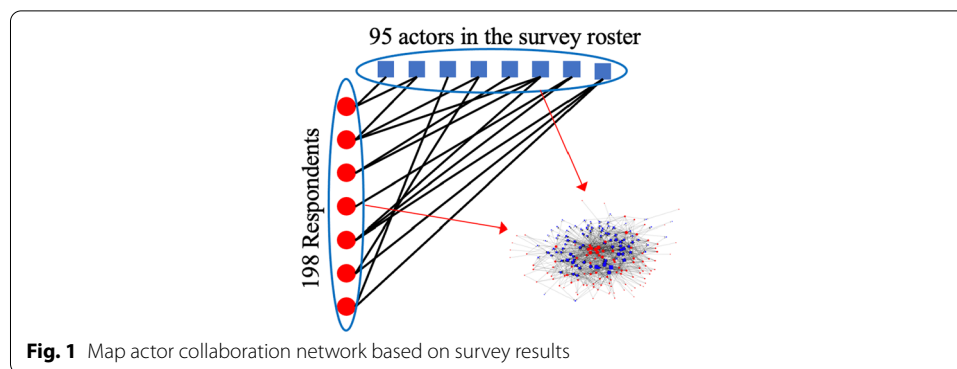


Table 2 Examples of departments and organizations in classified urban sectors

Category	Example of involved departments	Example of involved organizations
Flood control (FC)	Water departments and institutions, drainage, and floodplain management	The Texas Floodplain Management Association, Harris County Flood Control District, City of Houston Floodplain Management Office
Emergency response (ER)	Disaster management, disaster relief, fire department, police department, resilience offices	Harris County Office of Emergency Management, Texas Department of Public Safety, Federal Emergency Management Agency (FEMA)
Transportation (TT)	Transportation strategic planning, design, construction, and management departments	Metropolitan Transit Authority of Harris County (METRO), Houston TranStar, Port of Houston Authority, Texas Department of Transportation (TxDOT)
Community development (CD)	Business and economic services, academic institutions, public work departments, recreational departments	Houston Real Estate Council, United Way of Greater Houston, Harris County Community Economic Development Department, Bay Area Houston Economic Partnership
Environmental conservation (EC)	Pollution control, waste management	Bayou Land Conservancy, Bayou Preservation Association, Houston Wilderness, Urban Land Institute, The Nature Conservancy

actor collaboration network. Considering that monthly collaboration was the most representative answer, our analysis focused on the monthly collaboration network.

We assigned the actor preferences to flood risk reduction policy actions as attributes to the nodes of the mapped actor collaboration network. Each node could have one of three preferences states for each policy action: Oppose, Neutral and Support. In the data processing process, we grouped the survey results of “Strongly oppose” and “Oppose” and “Strongly support” and “Support.” Furthermore, we divided survey respondents into five urban sectors based on the organizations and departments they represented: community development (CD), flood control (FC), transportation (TT), environmental conservation (EC) and emergency response (ER) (Dong et al. 2020; Farahmand et al. 2020; Li et al. 2019, 2020c). Table 2 illustrates examples of classified urban sectors. The urban sectors of actors were also assigned to each node as one of the node attributes in the mapped collaboration network to examine the homophily effect. Table 3 summaries the node attributes that we accounted for in the mapped collaboration network.

Table 3 Considered node attributes in the network

Node attributes	Values
Urban sectors	CD, FC, TT, EC, and ER
Preference to P1	Oppose, neutral and support
Preference to P2	Oppose, neutral and support
...	
Preference to P16	Oppose, neutral and support

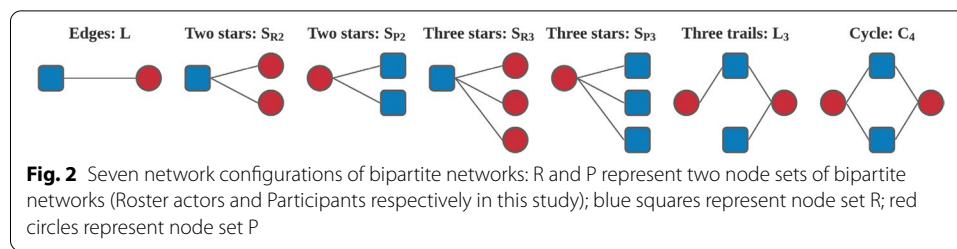
Methodology

The examination of the local interactions and homophily effects that form the social ties and contribute to the evolution of social networks are usually regarded as a bottom-up process (Boyd and Jonas 2001). As such, network motif analysis and ERGMs are suitable approaches for revealing the network configurations that encode the importation information related to tie and collaboration formation. Hence, we adopted network motif analysis for the examination of local interactions and ERGMs for the assessment of homophily effects in the actor network in the context of resilience planning and management of IISs in Harris County.

Network motif analysis

Network motifs are defined as the network structural elements in complex networks that have significantly larger counts compared with the random networks (Milo et al. 2002). Compared with the global network measures, network motifs reveal the patterns of local interactions, thus playing an important role in understanding the hidden mechanisms behind complex networks. Network motifs have been widely studied in social, neurobiology, biochemistry, financial, and engineering networks. To name a few studies, Dey et al. (2019) showed that distributions of network motifs (i.e., the patterns of local interactions) are strongly connected with the robustness of systems (e.g., power-grid networks, transportation networks). Saracco et al. (2016) detected the early-warning signs of the financial crisis through analyzing the motifs of the bipartite world trade networks. Schneider et al. (2013) studied the motifs of human mobility network and unraveled the mobility patterns. Gorochofski et al. (2018) studied organizations of 12 basic motif clusters in natural and engineered networks. The results showed that the organizations of motif clusters were different between networks of various domains. Robins and Alexander (2004) examined seven bipartite network configurations to study the small-world effects and distance in corporate interlocking networks. These examples highlight the growing use and capability of network motif analysis to study local interactions and hidden mechanisms that contribute to the robustness, organization, and functionality of complex networks.

In this study, we focused seven basic network configurations of bipartite networks without network projections, because studies showed that network projections may lose important information of bipartite networks (Robins and Alexander 2004; Zhou et al. 2007). Figure 2 illustrates seven network configurations of bipartite networks in

**Table 4** Statistics of network configurations of bipartite networks

Network configurations	Network statistics	Interpretation
Edges: L	$\sum_{R=1}^R \sum_{P=1}^P M_{RP}$	Number of edges in the bipartite network
Two stars: S_{R2}	$\sum_{R=1}^R \sum_{P' > P} M_{RP} M_{RP'}$	Correspondent to an edge between node set P in the 1-mode network
Two stars: S_{P2}	$\sum_{P=1}^P \sum_{R' > R} M_{PR} M_{PR'}$	Correspondent to an edge between node set R in the 1-mode network
Three stars: S_{R3}	$\sum_{R=1}^R \sum_{P'' > P' > P} M_{RP} M_{RP'} M_{RP''}$	Correspondent to a triangle between node set P in the 1-mode network
Three stars: S_{P3}	$\sum_{P=1}^P \sum_{R'' > R' > R} M_{PR} M_{PR'} M_{PR''}$	Correspondent to a triangle between node set R in the 1-mode network
Three trails: L_3	$\sum_{P' > P} \sum_{R' > R} M_{PR} M_{PR'} M_{P'R} (1 - M_{P'R'})$	Reflect global connectivity in bipartite networks
Cycle: C_4	$\sum_{P' > P} \sum_{R' > R} M_{PR} M_{PR'} M_{P'R} M_{P'R'}$	Local closures in bipartite networks

M_{RP} represents the value of the elements in the bi-adjacent matrix of the bipartite network. If node R and P are linked, $M_{RP} = 1$. Otherwise $M_{RP} = 0$

which the blue square and the red circle represent two-node sets. Table 4 shows the relative statistics and interpretations of the network configurations.

As illustrated in Table 4, Robins and Alexander (2004) introduced two new configurations, three trails and cycles, to study the local structures of bipartite networks. It is worth noting that these two configurations would lose the information of local interactions if we conducted network projections (three trails will become one edge and cycles will become one weighted edge). Therefore, it is essential to include these two network configurations for bipartite networks. Robins and Alexander (2004) argued that three trails could reflect the global connectivity of the bipartite network and cycles represent local closures in the bipartite network. For the bipartite networks with similar sizes and densities, more three trails and fewer cycles will increase the levels of connectivity and shorten the average path of the network, while more cycles and fewer three trails indicate stronger localized closeness. The bipartite clustering coefficient, $4 \times C_4/L_3$, could quantify the length of the average path and the strength of local interactions in the bipartite network.

Network motif analysis also involves comparing the numbers of network configurations in the examined network with those in random networks. In this research, we generated random bipartite networks with the same degree distributions and compared them with the examined network (Saracco et al. 2015). The configuration model that generated random graphs had fixed node degree distribution was regarded as one of the most insightful null models in monopartite networks (Chung and Lu 2002). We extended the configuration model to bipartite networks (Saracco et al. 2015). In this

analysis, we used sequential importance sampling to simulate bipartite networks with fixed degree distributions (Admiraal and Handcock 2008; Blitzstein and Diaconis 2011).

Although network motif analysis is a powerful method to investigate local interactions and reveal hidden mechanism behind complex networks for collaboration, it does not fully account for node attributes. Therefore, we adopted ERGMs to investigate the extent to which the node attributes affect the ties in the actor collaboration network.

Exponential random graph models (ERGMs)

ERGMs are a family of statistical models that could fit local structures or network configurations to model the network formations using maximum likelihood estimations (Wang et al. 2009). In a defined network space \mathcal{Y} that includes all possible networks with n nodes, a random network $Y \in \mathcal{Y}$, where $Y_{ij} = 0$ or 1 depending on whether the pair of nodes (i, j) are connected or not, then the probability of Y could be determined based on the counts of a set of network configurations. The general form of ERGMs could be written as follows:

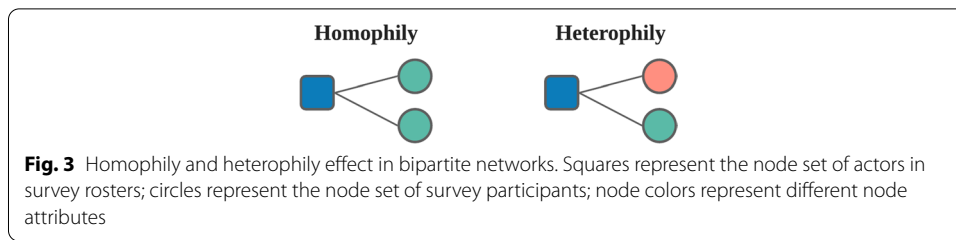
$$P(Y = y) = \frac{1}{k(\theta)} \exp\left\{\sum_{i=1}^p \theta_i S_i(y)\right\}, y \in Y \quad (1)$$

where $S_i(y)$ represents any user-defined network statistics measured on the network Y , and θ_i is associated parameters to be estimated. $k(\theta)$ is the normalizing constant to ensure the legitimacy of the defined probability distribution. Here, we provide a illustrative model inspired by Bomirha (2014) for the general readers. For an undirected friendship network in which edges represent mutual friendships and the network has probability p_1 between students living in the same dormitory and probability p_2 between students living in different dormitories. Then the ERGM model for investigating p_1 and p_2 could be written as follows:

$$P(Y = y) \propto \exp\left\{\theta_1 \sum_{i < j} y_{ij} + \theta_2 \sum_{i < j} y_{ij} I\{i \text{ and } j \text{ lives in the same dormitory}\}\right\} \quad (2)$$

The first set of statistics in Eq. (2) represent the number of edges; the second set of statistics is the number of edges connecting nodes living in the same dormitory. Based on this model, we can easily derive p_1 equals to $e^{\theta_1 + \theta_2} / (1 + e^{\theta_1 + \theta_2})$ and p_2 equals to $e^{\theta_1} / (1 + e^{\theta_1})$. Furthermore, the coefficient θ_2 could show the homophily (with $\theta_2 > 0$) or heterophily (with $\theta_2 < 0$) effect in the studied friendship network. More in-depth discussion regarding the theory of ERGMs could be found in Robins et al. (1999, 2007) and Wang et al.'s works specifically for bipartite networks (2009).

ERGMs provide a powerful tool for generating quantitative evidence for the tie formation process related to network configurations and node attributes. The existing literature has adopted ERGMs to study the dynamics and mechanisms of social tie formations behind different kinds of networks, such as collaborative networks (Nohrstedt and Bodin 2019), partnership networks for urban development (McAllister et al. 2015), inter-organizational knowledge sharing networks (Broekel and Hartog 2013), Facebook friendship networks (Traud et al. 2011, 2012; Wimmer and Lewis 2010), and hospital networks of patient transfers (Lomi and Pallotti 2012). In this paper, we focus on the examination of the homophily effect in the actor collaboration network in resilience planning and management of interdependent infrastructure systems. Homophily in the bipartite networks



is represented by two neighbors with the same attributes connected to the same node (illustrated in Fig. 3) because they cannot directly connect with each other (Bomiriha 2014). We adopted network statistics developed by Bomiriha (2014) to model homophily for bipartite networks. Equation 3 illustrates included network statistics.

$$P(Y = y) \propto \exp \left\{ \begin{array}{l} \theta_1 \text{edges} + \theta_2 * \text{nodematch}(\text{urban sector CD}) + \dots + \\ \theta_6 * \text{nodematch}(TT) + \theta_7 * \text{nodematch}(P1) + \dots + \\ \theta_{22} * \text{nodematch}(P16) \end{array} \right\} \quad (3)$$

In Eq. 3, edges represent network statistics of edges in the mapped bipartite network. Nodematch (urban sector CD) represents network statistics of two survey respondents in the same urban sector, community development (CD), collaborating with the same actor in the survey roster. Likewise, nodematch (P1) represents network statistics of two survey respondents both supporting policy action P1 collaborating with the same actor in the survey roster. The detailed calculations of network statistics (i.e., nodematch) could refer to the R package: *ergm* (Hunter et al. 2008). The parameters in Eq. 3 were estimated by Monte Carlo maximum likelihood estimation. Therefore, the parameters $\theta_2 \sim \theta_{22}$ could show the homophily effect with positive values and the heterophily effect with negative values.

Results

The network motif analysis shows that the actor collaboration network has strong local interactions. Figure 4 illustrates the network configurations in the observed network and those in the simulated 1000 random models. Table 4 shows the detailed statistics of network configurations in the observed network as well as mean values and standard deviations in the random models.

From Fig. 4 and Table 5, we can find that the observed actor collaboration network has significantly fewer three trails (Z-score: -15.4) and more cycles (Z-score: $+6.51$) compared with the simulated random models. Also, the local clustering coefficient of the observed actor collaboration network is significantly higher (Z-score: $+15.83$) than the simulated random models. Apparently, the algorithm that we applied, *Networksis* package in R, fixed the number of edges, two stars, and three stars to generate the random models with same degree distributions (Admiraal and Handcock 2008). The results of the motif analysis indicate that: (1) there are hidden mechanisms and additional social processes to form the collaborations among actors due to significantly different counts of three trails and cycles compared with the random models; and (2) the observed actor collaboration network has a long average path length and strong local interactions due to its fewer three trails, more cycles, and higher

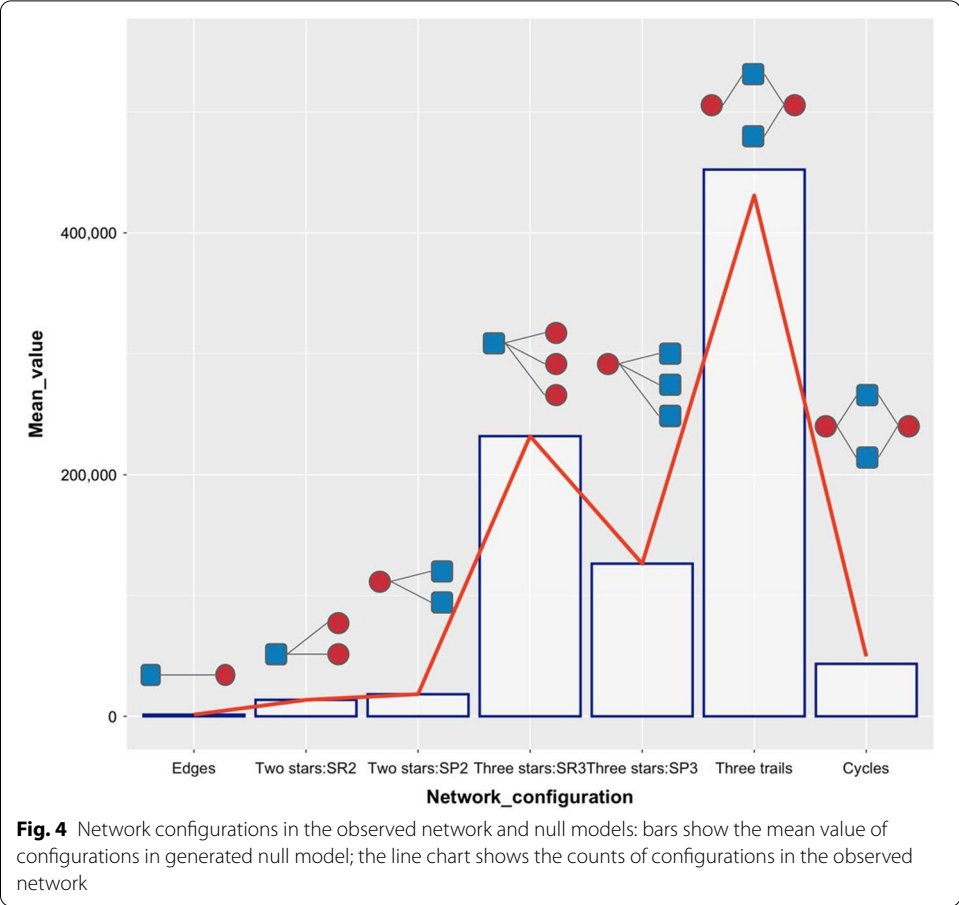


Table 5 Statistics of network configurations in the observed network and null models

Statistics	Observed network	Simulated models	Z-score
Edges: L	1414	1414 (0)	0
Two stars: S_{R2}	13,635	13,635 (0)	0
Two stars: S_{P2}	18,302	18,302 (0)	0
Three stars: S_{R3}	231,964	231,964 (0)	0
Three stars: S_{P3}	126,400	126,400 (0)	0
Three trails	430,999	452,387 (1393)	− 15.4
Cycles	49,626	43,464 (946)	+ 6.51
Clustering Coefficient: $4 \times C_4/L_3$	0.46	0.384 (0.0048)	+ 15.83

For the simulation models, numbers in the parentheses are standard deviations and number outside the parentheses are mean values

clustering coefficient compared with the random models. The results imply that the formations of the actor collaborations are due to strong local interactions, such as collaborations in the same urban sectors or collaborations among actors with same policy preferences. Also, collaborations outside the local clusters are limited due to their long average network path length. The ERGMs could help in further investigations of the factors affecting the actor collaboration.

The ERGMs demonstrate both significant homophily effects and heterophily effects for actor collaboration in resilience planning and management of IISs. The results show the significant homophily effects within the transportation sector, significant heterophily effects within the emergency response sector, and varied homophily and heterophily effects due to different flood risk reduction policy actions. This finding implies that: (1) the actors in the transportation sector are less likely to build collaboration ties with actors from other urban sectors; and (2) emergency response actors are likely to form collaboration ties with actors of other sectors. Table 5 shows the estimated coefficients of variables in ERGMs. We include the Markov Chain Monte Carlo (MCMC) diagnostic plots in the supplementary information. The plots were obtained from randomly generated networks from the fitted models. The MCMC diagnostic plots showed evidence of random variation and approximately normal-shaped distributions centered at zero, which are consistent with good performance in model fitting (Bomirih 2014).

We can observe from Table 6 that the probability of edges is $e^{-2.8619} = 0.057$, excluding all the homophily effects in the table, which is lower than the density of the observed network: 0.0756. This result implies that the structure of the observed network is shaped by homophily effect, which is consistent with the results of network motif analysis that the network showed a strong local interaction effect (actors of the same sector are more likely to collaborate with each other). Also, we found that actors from the emergency response sector (ER) showed significant heterophily effects. When an actor from

Table 6 Estimated coefficients of variables in ERGMs

Variables	Estimate	SD	p value
Edges	− 2.862	0.160	< 0.0001***
Urban sector: CD	0.146	0.308	0.6358
Urban sector: EC	− 0.074	0.276	0.7887
Urban sector: ER	− 0.988	0.283	0.0005***
Urban sector: FC	0.006	0.280	0.9818
Urban sector: TT	1.297	0.295	< 0.0001***
P1: support	− 1.517	0.212	< 0.0001***
P2: support	0.531	0.153	0.0005***
P3: support	− 0.381	0.212	0.0730*
P4: support	− 0.007	0.213	0.9739
P5: support	0.182	0.149	0.2225
P6: support	− 0.137	0.159	0.3859
P7: support	− 0.820	0.158	< 0.0001***
P8: support	1.193	0.197	< 0.0001***
P9: support	0.681	0.153	< 0.0001***
P10: support	− 0.428	0.238	0.0717*
P11: support	0.801	0.252	0.00015**
P12: support	− 0.602	0.145	< 0.0001***
P13: support	0.148	0.135	0.2729
P14: support	− 0.773	0.165	< 0.0001***
P15: support	0.463	0.213	0.0298**
P16: support	1.452	0.176	< 0.0001***

***significant at 99%, **significant at 95%, *significant at 90%; here support combines survey response strongly support and support

ER collaborates with an actor in the survey roster, another actor from the emergency response sector would have reduced probability ($e^{-2.8619-0.9879}=0.021$) to collaborate with the same actor in the survey roster. This result is consistent with the real situation that actors from the emergency response sector usually collaborate with actors from other sectors (e.g., flood control and transportation sectors) for hazard mitigation during disasters. Furthermore, the actors from the transportation sector (TT) showed significant homophily effect. When an actor from the transportation sector collaborates with the actor in the survey roster, another actor from the transportation sector would have increased probability ($e^{-2.8619+1.2971}=0.209$) to connect with the same actor in the survey roster. This result shows strong local interactions in the transportation sector. The results are also consistent with our former studies regarding actor collaboration within and across different urban sectors for hazard mitigation and resilience planning of IISs (Li et al. 2019). Actors from the transportation sector showed the highest within-sector collaboration, while actors from the emergency response had highest across-sector collaborations. However, we cannot see significant homophily effects in other urban sectors, such as the community development (CD), environmental conservation (EC) and flood control (FC) sectors. This result may imply that the formation of collaboration is not purely due to the organizational proximity.

We also found significant heterophily effects in some flood risk reduction policy actions including P1 (Limit new development), P3 (Strengthen infrastructure), P7 (Build levees), P10 (Improve stormwater system), P12 (Temporarily prohibit development after disasters), and P14 (Limit development of public facilities). The actors have preferences to these policy actions had significantly reduced probability to collaborate with the same actors in the survey roster. Based on the structural hole theory, this heterophily effect may suggest collaboration among these actors was sought to increase bridging capitals, to seek exotic resources and skills to advance their positions, and to broaden the influence in the network (Burt 2004; Lazega and Burt 1995; McAllister et al. 2015). We also found significant homophily effects in some flood risk reduction policy actions, including P2 (Elevate buildings), P8 (Build reservoirs/retention ponds), P9 (Protect wetlands/open space), P15 (Limit rebuilding in frequent flooding areas), and P16 (Buy out or acquire property). The actors indicating preferences to these policy actions had a significantly increased probability to collaborate with the same actors in the survey roster. The intent of collaboration among these actors was to increase the bonding capital and to reinforce shared norms and trusts (McAllister et al. , 2015).

Discussion

The results did not indicate that the urban sectors of actors were a pure driver to form the collaborations among actors. Actors from the flood control, environmental conservation, and community development sectors did not show significant homophily effects in formation of ties. The results indicated that actors from emergency response sectors had significant collaboration with actors from other urban sectors. Previous studies showed that emergency response actors, such as Houston Fire Department, Harris County Office of Emergency Management, and Texas Department of Public Safety, collaborated with actors from other sectors, including environmental conservation, community development, and transportation sectors, for first response and recovery during

and after disasters (Li et al. 2019). Existing studies also highlighted the importance of collaboration among actors from diverse sectors for effective emergency response and disaster recovery (Aldrich 2012; Campanella 2006; Gajewski et al. 2011). The results also showed strong within-sector collaborations for actors from the transportation sector. The transportation sector in Texas has great and wide-ranging authority and is a leading voice in infrastructure development driven by real estate development. Transportation planning in Texas, however, lacks resilience metrics for the long run. Furthermore, the transportation sector has its own planning and environmental affair divisions, which may contribute to its limited collaboration with other urban sectors. The results of network motif analysis showed that the collaboration network has a long average path length and strong local closeness, which also implied that actors from the transportation sector have strong local interactions but limited collaboration with actors from other sectors. A lack of collaboration with actors from the flood control sector, however, may lead to urban growth without compatible investments on flood control infrastructures. Also, insufficient collaboration between flood control and transportation sectors may lead to infrastructure development in hazard-prone areas.

The results of network motif analysis and homophily effects of actors from urban sectors in ERGMs are consistent with the planning background in the Houston area. Houston repeatedly suffers from extensive damage due to major flood events (Boburg and Reinhard 2017; Patterson 2017). One major reason is rapid urban growth without holistic planning for flood risks. On one hand, Houston plans growth primarily by developing major institutional projects, building expansive infrastructure networks, and encouraging neighborhood-level planning through super neighborhood organizations (Neuman and Smith 2010). Also, Houston adds density bonuses to encourage development in the urban core (Fulton 2020). Although these policies support population growth (Masterson et al. 2014; Qian 2010), they also exacerbate flooding vulnerability (Zhang et al. 2018). On the other hand, Houston mitigates flood risk with projects such as the Bayou Greenways Initiative to protect and enhance the network of connected open spaces along bayous (Blackburn 2020), development of structural surge infrastructure, and coastal ecosystem enhancement along Galveston Bay (Blackburn 2017), construction and restoration of detention ponds, supporting home buyouts (Harris County Flood Control District 2017), and retrofitting critical flood control infrastructures through the Hazard Mitigation Plan (Harris County Flood Control District 2017). Planning in Houston, however, is driven largely by the real estate development serving the desire for economic growth. Houston lacks a compatible planning crosswalk between urban growth and the investment on flood control infrastructure, which requires the involvement and collaboration of diverse stakeholders from urban sectors and scales. The findings of this study showed the need for a greater cross-sector collaboration to expand local interactions, as well as the important roles certain actors could play to span boundaries and bridge ties among actors of various sectors with similar and dissimilar preferences to flood risk reduction policy actions.

Furthermore, we found both significant homophily and heterophily effects in actor preferences to flood risk reduction policy actions in ERGMs. The results indicated mixed mechanisms for collaboration among actors. The heterophily effect indicates that a part of actor collaboration was to increase the bridging capitals, to seek exotic resources and skills

to advance the positions, and to broaden the influence in the network. The involved actors usually play a brokage role in the collaboration network, helping connect different actors from diverse urban sectors. Based on network measures, such as betweenness centrality, we can identify these actors in the collaboration network (Li et al. 2020c). The homophily effect indicates that a part of collaboration was to increase bonding capitals, reinforcing shared norms and trusts. The involved actors usually are in the core of networks or local clusters. We can identify these actors in the collaboration network through core-periphery analysis and community detection (Li et al. 2020a; c). The ERGMs provide insights into the mechanisms for collaboration among diverse actors, helping to develop strategies to increase network cohesion and to improve collaboration among actors from diverse urban sectors.

The results of the study highlight some resilience characteristics embedded in human systems for urban resilience governance. The first is multi-scale governance (Paterson et al. 2017; Wagenaar and Wilkinson 2015). Urban resilience requires multi-level collaborations across complex boundaries at social, physical, and ecological dimensions (Boyd and Juhola 2015; Li et al. 2020b). Also, resilience planning is the outcome of interdependent plans at different scales (e.g., city, regional, state, and federal). In a study of resilience practitioners in 20 cities, Fastiggi et al. (2021) pointed out that external collaborations, such as multi-disciplinary consultants, advisory committees, resilience consortiums, and peer networks, would be of great help in improving multi-governance for urban resilience governance. Another resilience characteristic is the knowledge co-production and trust (van der Jagt et al. 2017). Existing literature stressed the importance of diverse stakeholder engagement to improve knowledge co-product and trust in urban resilience governance (Graversgaard et al. 2017; Nutters and Pinto da Silva 2012; Watson et al. 2018; Wiesmeth 2018). The inclusion of diverse stakeholders across various urban sectors would improve the collective understanding of complex systems, solve conflicts, and enhance shared values.

Furthermore, given that existing studies usually examined these resilience characteristics separately, Dong et al. (2020) proposed the institutional connectedness for effective urban resilience governance, accounting for three synergistic areas embedded in human systems: the actor collaboration of actor networks, the plan integration of networks of plans, and the shared norm and values. Our study provides a new way to examine the actors' network and their attributes simultaneously. The level of local interactions could shed lights on the need for external collaborations, and ERGMs provides insights into policies and norms for actor collaborations. Furthermore, institutional connectedness stresses shared norms among actors to increase network cohesion and actor collaborations for resilience governance. In our study, we found that the heterophily effect is also an important factor for tie formation in actor collaboration networks. The result is consistent with those from existing studies that highlighted the heterophily effect for the tie formation in different types of social networks (Barranco et al. 2019; Kimura and Hayakawa 2008; Lozares et al. 2014).

Concluding remarks

In this paper, we examined two important mechanisms, local interactions and homophily effects for actor collaboration in resilience planning and management of IISs. We conducted a stakeholder survey to collect data regarding actor collaboration for resilience

planning of IISs and actor preferences to a list of flood risk reduction policy actions. We mapped the bipartite network and adopted network motif analysis and ERGMs to investigate network configurations and related node attributes, which encode important information of collaboration among actors. The paper has both theoretical and practical contributions: (1) we combined network motif analysis and ERGMs models which both focus on the network configurations and a bottom-up process in the formation of social networks. The results of network motif analysis and ERGMs have different focuses and could be complementary to each other. (2) The study could provide empirical evidence regarding drivers of collaboration among diverse actors in resilience planning and management of IISs. These results could help develop strategies to foster collaboration among actors from diverse urban sectors involved in the process of resilience planning and management of IISs.

This study and its findings complement the existing literature related to actor collaborative network analysis in collective action problems related to disaster management and environmental governance by the examination of two mechanisms contributing to network formation and evolution: local interactions and the homophily effect. Many of the existing studies primarily focused on topological properties of actor networks but did not fully account for actor node attributes. The combined analysis of network structure and node attributes (i.e., sectors and policy preferences of actors) and findings provide deeper insights into the institutional connectedness of human systems that influence urban resilience. In addition, this study contributes to the field of urban resilience planning and management of IISs by advancing the empirical understanding of actors' network properties and the underlying mechanisms that govern the creation of ties/links in actor collaboration networks.

The study has some limitations. First, we did not consider dynamic network evolutions in this paper due to the lack of longitudinal data. Future study could collect actor collaboration data after Hurricane Harvey to investigate the extent to which local interactions and homophily effects affect the network evolution after the disaster like Hurricane Harvey in the collaboration network. Second, we found significant homophily and heterophily effects for preferences to different risk reduction policy actions; however, we did not explore whether the policy actions led to the homophily or heterophily effects. Future studies could explore the reason based on the essential knowledge of public policies. Third, we applied an algorithm to generate random networks with fixed degree distributions. The algorithm fixed the counts of edges, two stars, and three stars, which lost some information of the network motif analysis. Although Saracco et al. (2015) noted that higher-order network motifs (e.g., three trails and cycles) encode much more network information compared with the lower-order network motifs, future studies could test and apply different algorithms to examine the significance of network motifs.

Abbreviations

IISs: Interdependent infrastructure systems; ERGMs: Exponential random graph models; CD: Community development; FC: Flood control; TT: Transportation; EC: Environmental conservation; ER: Emergency response; FEMA: Federal Emergency Management Agency; TxDOT: Texas Department of Transportation; METRO: Metropolitan Transit Authority of Harris County; MCMC: Markov Chain Monte Carlo.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1007/s41109-021-00433-z>.

Additional file 1. Supplementary Information for the Local Interactions and Homophily Effects in Actor Collaboration Networks for Urban Resilience Governance.

Acknowledgements

The authors would like to thank Jan Gerston for her copy-editing service.

Authors' contributions

QL and AM designed the study. QL processed the data, conducted the analysis, and visualized the results. QL wrote the manuscript and AM reviewed the manuscript. All authors read and approved the final manuscript.

Funding

The study is supported by the National Science Foundation RAPID project # 1760258: RAPID: Assessment of Risks and Vulnerability in Coupled Human-Physical Networks of Houston's Flood Protection, Emergency Response, and Transportation Infrastructure in Harvey. CRISP 2.0 project # 1832662: Anatomy of Coupled Human-Infrastructure Systems Resilience to Urban Flooding: Integrated Assessment of Social, Institutional, and Physical Networks. Any opinions, findings, conclusions, or recommendations expressed in this research are those of the authors and do not necessarily reflect the view of the funding agency.

Availability of data and materials

The raw data in this study are not publicly available due to the requirements of Institutional Review Boards. The derived and anonymized data are available in the Github repository: <https://github.com/Qingchun-Li/Local-Interactions-and-Homophily-Effects-in-Actor-Collaboration-Networks-for-Urban-Resilience-Govern>.

Declarations

Ethics approval and consent to participate

The stakeholder survey conducted in the study was approved by Texas A&M University Human Subjects Protection Program office, and the written consent was obtained (IRB ID: IRB2017-0961M, Reference Number: 068583). Please contact the Ethics Committee (contact via Texas A&M University Human Subjects Protection Program office at 855-795-8636 or email at irb@tamu.edu) for researchers who meet the criteria for access to the confidential raw data.

Consent for publication

Not applicable.

Competing interests

The authors declare that they have no competing interests.

Received: 5 July 2021 Accepted: 30 October 2021

Published online: 19 November 2021

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