COMMUNITY RESILIENCE TO WILDFIRES

A Network Analysis Approach by Utilizing Human Mobility Data

Qingqing Chen, Boyu Wang, Andrew Crooks

INTRODUCTION

Disasters, such as wildfires, has been a long-standing concern to societies, which often result in significant impacts on the environment, wildlife, and human populations. Therefore, understanding the impacts and resilience of areas that are often exposed to such events has become essential. *We propose a novel framework to capture impacts of dynamic disruptions of a disaster to assess a community's resilience to wildfires in a long-term period.*

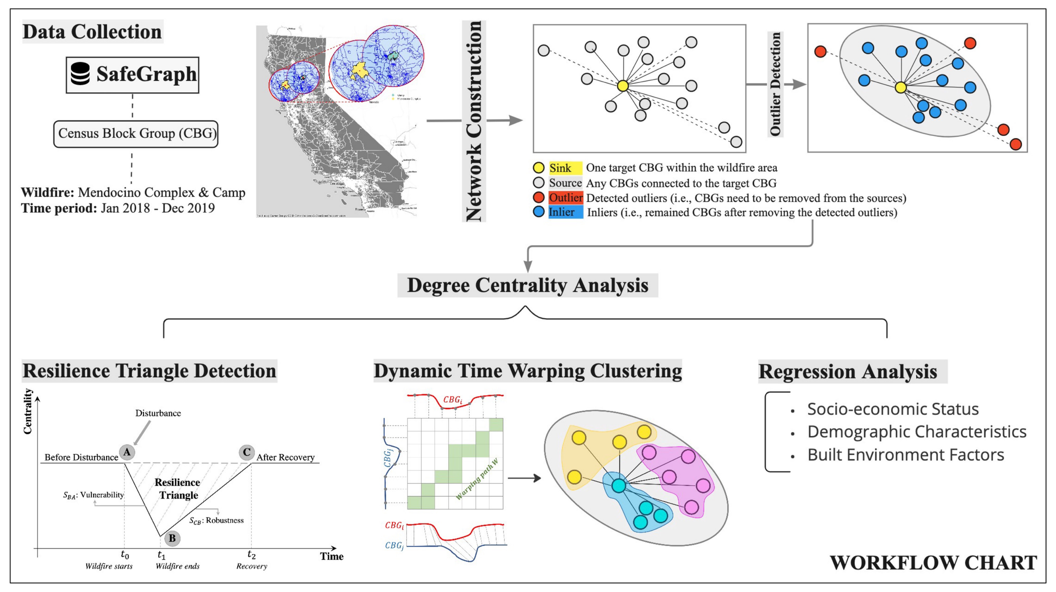

Figure 1. An overview of the research workflow.

METHODS

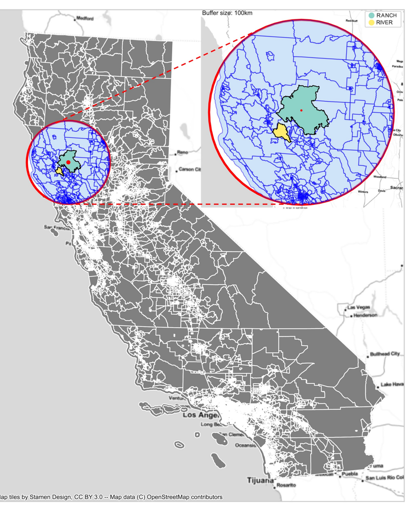

Figure 2. Study area.

We selected Mendocino Complex & Camp wildfires as test cases and utilized a human mobility data collected from SafeGraph between Jan 2018 and Dec 2019 to quantify resilience of communities at census block (CBG) level by leveraging network analysis and the concept of resilience triangle from disaster science.

STEP 1: Network Construction

- Degree centrality: an index of exposure to what is flowing through the network.
- Used for evaluating the degree of importance of specific nodes or links in a network
- A CBG as a node; connections between two CBGs as a link weighted by the frequency of visitation between the two.
- A node with high degree centrality indicates higher probability to be disrupted when being hit by a disaster (Sharifi., 2019).

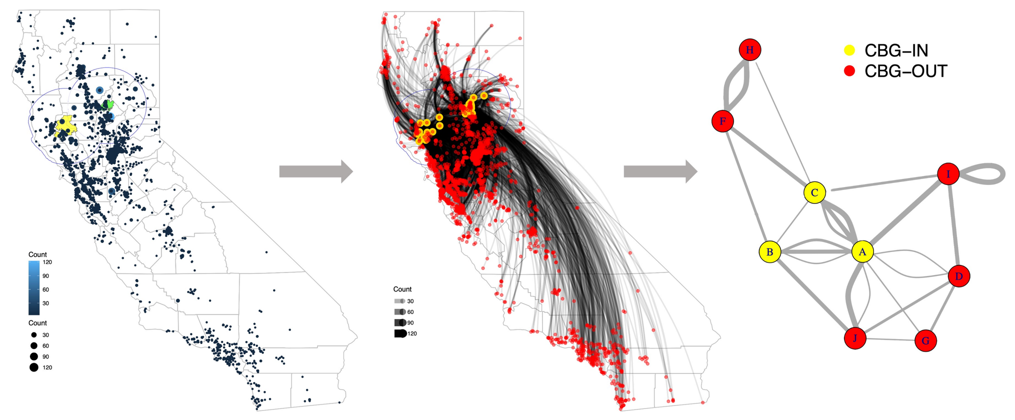

Figure 3. An example of network construction.

STEP 2: Resilience Triangle Detection

- The resilience triangle (Bruneau et al., 2003) records the abrupt losses in performance of a social unit under the disruption of a disaster.

Depth: the severity of the disruption
Length: the recovery time
Area: resilience of the social unit. The smaller the area is, the more resilience the social unit is.

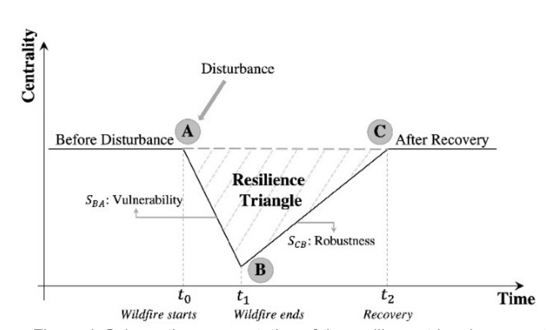

Figure 4. Schematic representation of the resilience triangle concept.

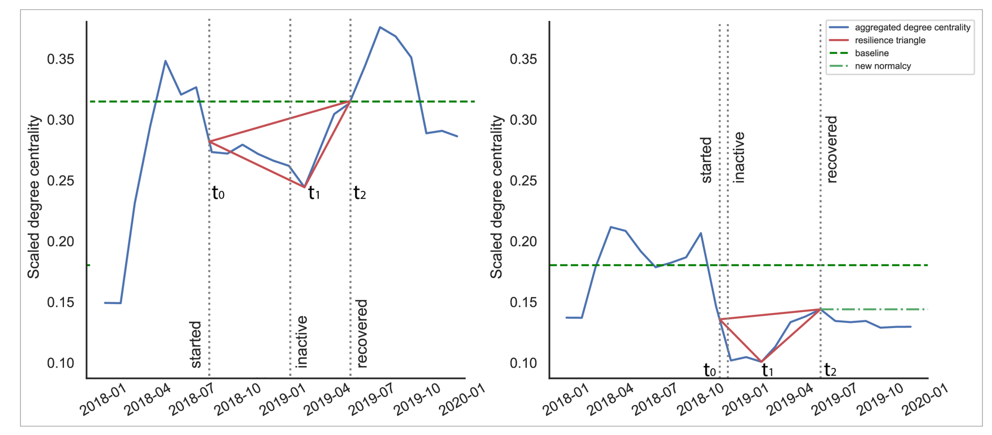

Figure 5. Examples of identified resilience triangles.

STEP 3: Dynamic Time Warping Clustering

- DTW clustering is known as an accurate method for clustering time series data (Wang et al., 2013).
    - Each CBG can have a different response and recovery pattern of degree centrality.
    - Classify CBGs based on changing patterns to evaluate the similarity.

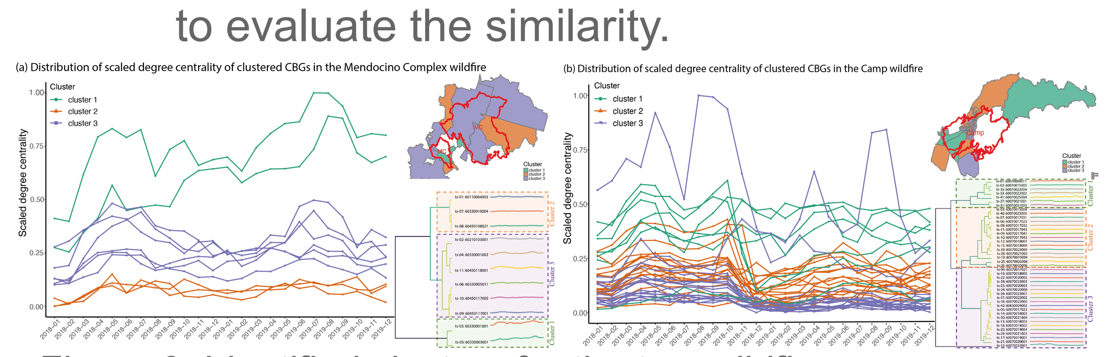

Figure 6. Identified clusters for the two wildfires.

STEP 4: Regression Analysis

- Provide an initial quantitative exploration of the potential underlying covariance that impact community resilience.

Table 1. Description of independent variables

Avg Distance	Average distance from home CBG to a target CBG
% Pop Dist < 3km	Percentage of population travel within 3 km from home CBGs to a target CBG
Area in Wildfire	The area of a target CBG within the wildfire area
# of Housing Units	Number of housing units of a target CGB
Med Household Income	Median household income of a target CBG
Med Age Male	Median age of male of a target CBG
Med Age Female	Median age of female of a target CBG
# of workers	The number of full-time workers in a target CBG
% Pop > Undergraduate	The percentage of people that are undergraduate or higher of a target CBG

Results

Mendocino Complex Wildfire

- **Cluster 1** (most resilient): smallest % of population stay within 3km; smallest area within the wildfire; people are relatively younger
- **Cluster 2**: the smallest # of housing units; the smallest # of full-time workers, highest median household income; people are relatively elder
- **Cluster 3** (least resilient): largest area within the wildfire; largest % of population stay within 3km; high # of housing units; people are relatively elder

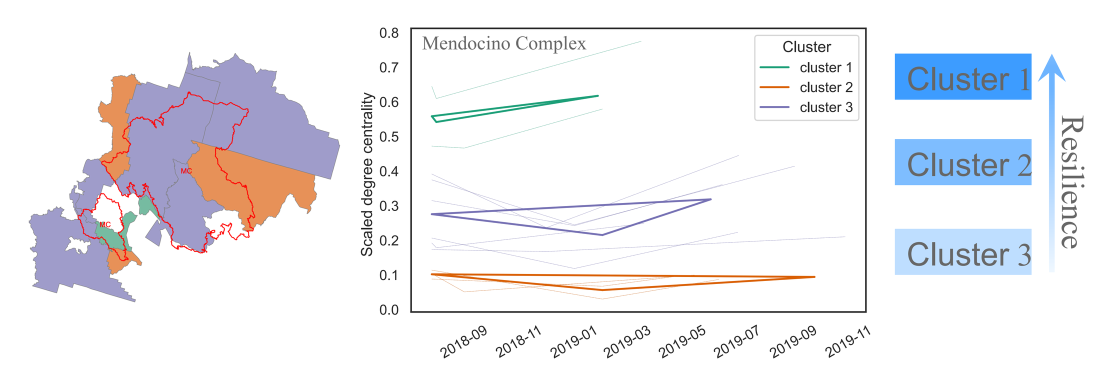

Figure 7. Resilience of different CBG clusters in MC wildfire.

Camp Wildfire

- **Cluster 3** (most resilient): smallest area within the wildfire; smallest # of housing units & full-time workers; relatively high median household income
- **Cluster 2**: relatively small area within the wildfire; small # of housing units & full-time workers
- **Cluster 1** (least resilient): largest area within the wildfire; largest # of housing units & full-time workers; highest median household income; people are relatively younger

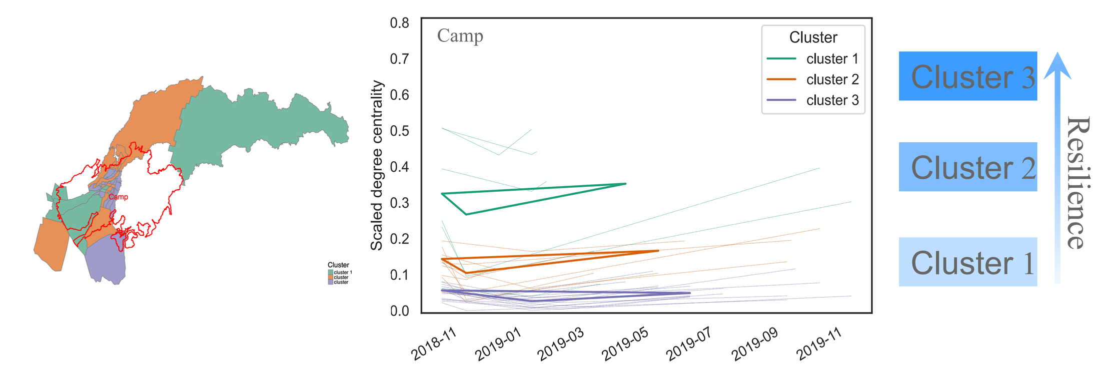

Figure 8. Resilience of different CBG clusters in Camp wildfire.

Conclusion

Quantifying community resilience is an open research challenge. Our results show community resilience is highly related to demographic characteristics, socio-economic status.

- **Scales up the concept of resilience to a more empirical framework that can be quantified and visualized.**
- **Paves a way to study disasters and their long-term impacts on society.**

Acknowledgements

This work was supported by the Center for Geological and Climate Hazards Studies at University at Buffalo. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the author(s) and do not reflect the views of the Center. We would also like to thank Dr. Yingjie Hu for providing data for this study.

References

1. Sharifi, A., 2019. Resilient urban forms: A review of literature on streets and street networks. *Building and Environment* 147, 171–187.
2. Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A., von Winterfeldt, D., 2003. A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra* 19, 733–752.
3. Wang, X., Mueen, A., Ding, H., Trajcevski, G., Scheuermann, P., Keogh, E., 2013. Experimental comparison of representation methods and distance measures for time series data. *Data Mining and Knowledge Discovery* 26, 275–309.

University at Buffalo The State University of New York

Department of Geography, College of Arts and Sciences
qchen47@buffalo.edu
@qingqingchen77