Community Resilience to Wildfires

A network analysis approach by utilizing human mobility data


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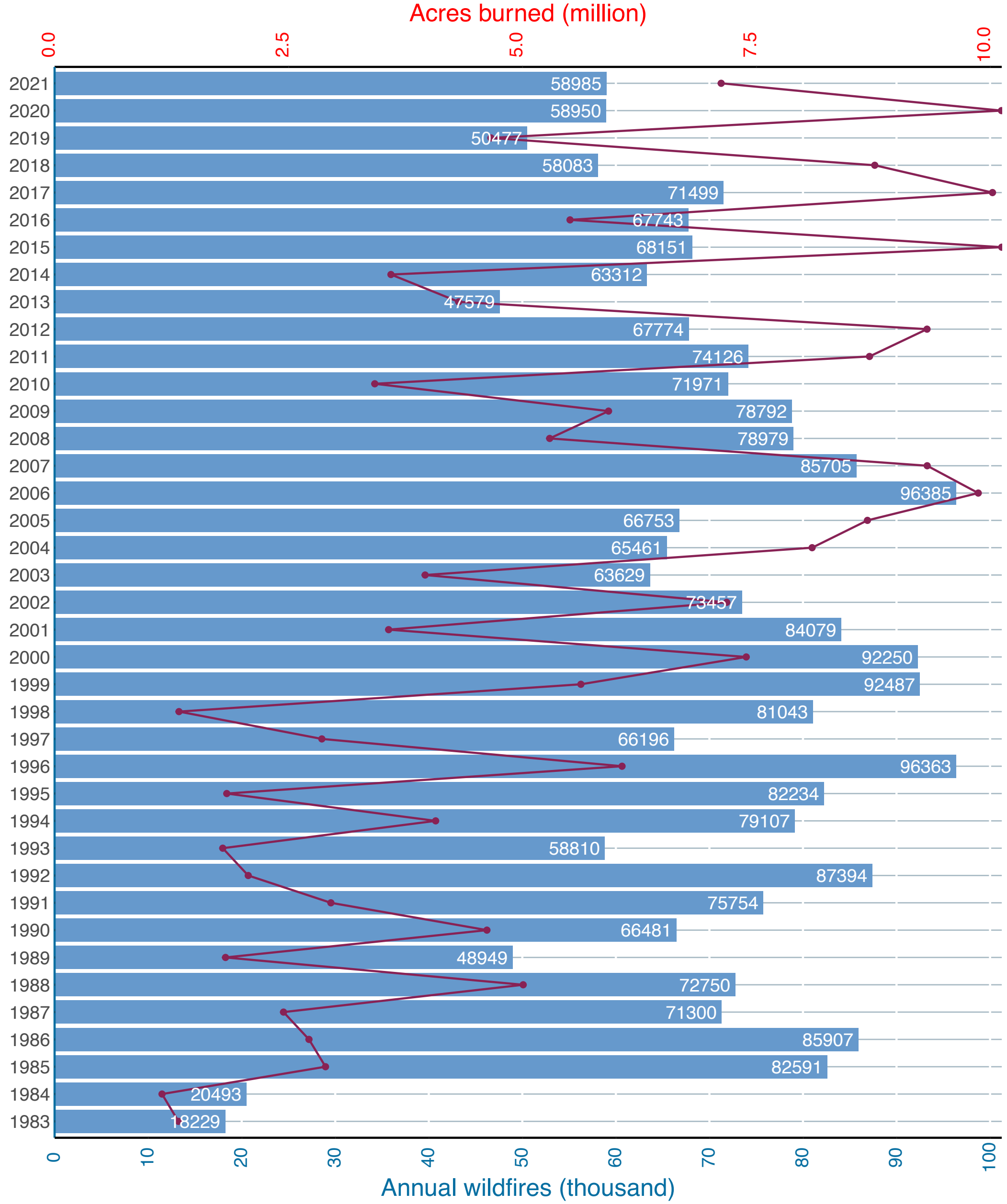
Distribution of annual wildfires and acres in the United States

1983–2021 (source: the National Interagency Fire Center (NIFC))



Creator: Noah Berger | Credit: AP

Resilience

How well a system can re-establish stability and functions from the disruption of a disaster over time.

National Academies, 2012. Disaster resilience: A national imperative. Na- tional Academies Press, Washington, D.C.

Resilience

How do we quantify resilience to disasters?

- Developing *indices* derived from different resilience determinants (e.g., social, economic, infrastructure, environment)
  - Baseline Resilience Index for Communities (BRIC) (Cutter et al., 2010)
  - Community Disaster Resilience Index (CDRI) (Peacock et al., 2010)
  - Resilience Capacity Index (RCI) (Foster, 2012)

Comparative across space

No standard evaluation
Unclear contribution of metrics
View resilience statically

- Understanding how *people behave and interact* with the built and natural environment
  - The role of social relationships in supporting and adaptation in disasters (e.g., Bolin, 2007)
  - Understand how people react to stresses in disasters (e.g., Fritz and Marks, 1954),
  - Social/place attachments (e.g, Bukvic et al., 2022)
  - Decision-making (e.g., Rosenstein, 2004)

Multidimension: social norms, psychology, social attachment

Theoretical construction/conceptual modeling
Empirical validation largely remains unexplored

Bolin, B., 2007. Race, class, ethnicity, and disaster vulnerability, in: Rodr ́ıguez, H., Quarantelli, E.L., Dynes, R.R. (Eds.), Handbook of Disaster Research. Springer, New York, NY. Handbooks of Sociology and Social Research, pp. 113–129.
Cutter, S.L., Burton, C.G., Emrich, C.T., 2010. Disaster resilience indicators for benchmarking baseline conditions. Journal of Homeland Security and Emergency Management 7.
Peacock, W., Samuel, B., Seitz, W., Merrell, W., Vedlitz, A., Zahran, S., Harriss, R., Stickney, R., 2010. Advancing resilience of coastal localities: Developing, implementing, and sustaining the use of coastal resilience indicators: A final report.
Fritz, C.E., Marks, E.S., 1954. The NORC studies of human behavior in disaster. Journal of Social Issues 10, 26–41
Bukvic, A., Whittemore, A., Gonzales, J., Wilhelmi, O., 2022. Understanding relocation in flood-prone coastal communities through the lens of place attachment. Applied Geography 146, 102758.
Foster, K., 2012. Urban and regional policy and its effects: Building resilient regions. Brookings Institution Press.
Rosenstein, D.L., 2004. Decision-making capacity and disaster research. Journal of Traumatic Stress 17, 373–381.

Web 2.0

- Data at an unprecedented scale with geolocation feature
- Spatio-temporally precise and accurate
- Shifts resilience research towards a more data-driven direction

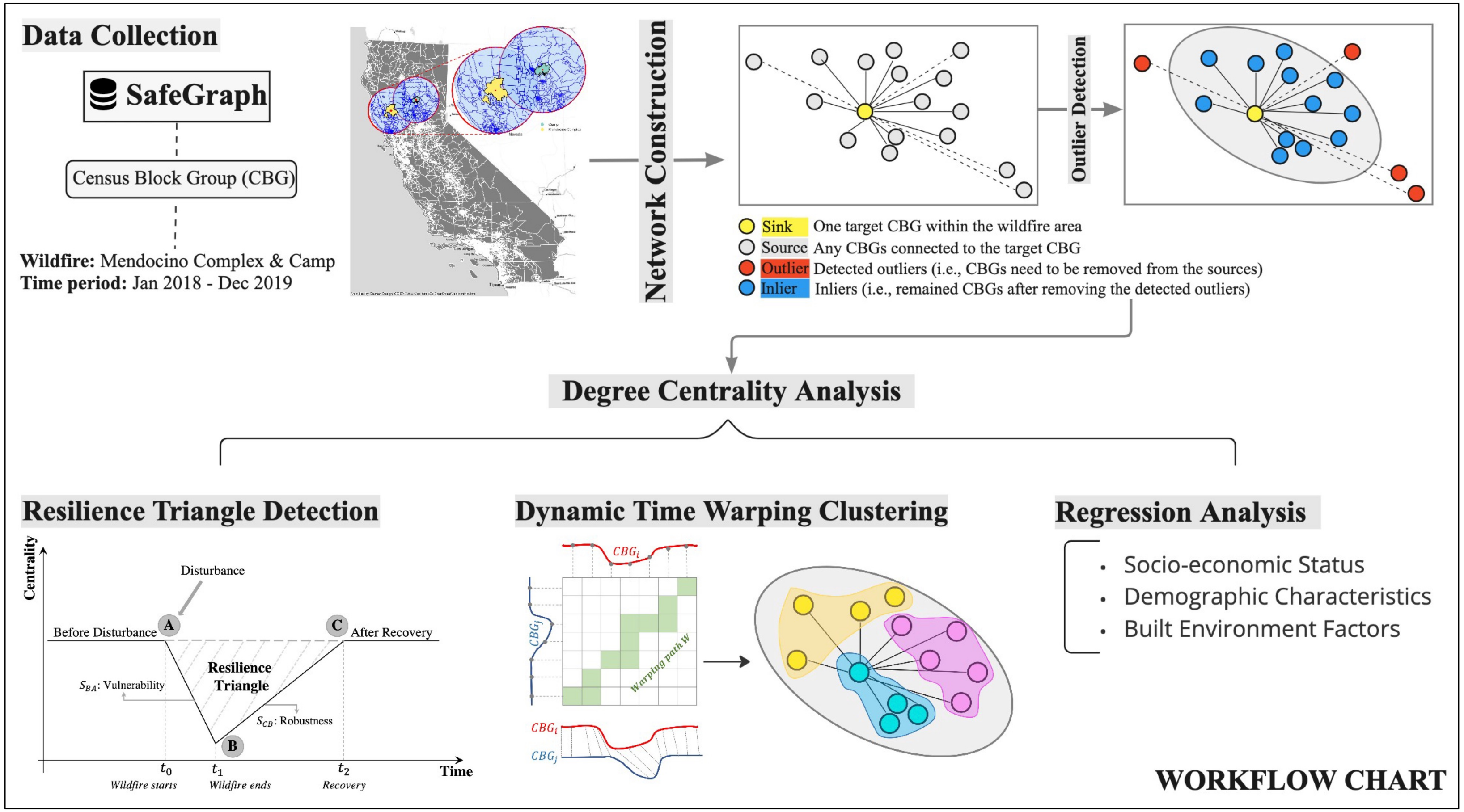
- ➢ Sentiment analysis techniques to investigate people's opinions to disasters (e.g.., Yuan et al., 2021).
- ➢ Human mobility analysis to monitor and compare individuals' movements and behavioral responses to a disaster (e.g., Yabe et al., 2002)

Potential & flexibility of using mobility data to connect disaster information & people;
Enhancing the understanding of disaster resilience.

Short-term analysis
Long-term period study is still a challenge

Yuan, F., Li, M., Liu, R., Zhai, W., Qi, B., 2021. Social media for enhanced understanding of disaster resilience during Hurricane Florence. International Journal of Information Management 57, 102289
Yabe, T., Zhang, Y., Ukkusuri, S.V., 2020. Quantifying the economic impact of disasters on businesses using human mobility data: a Bayesian causal inference approach. EPJ Data Science 9, 1–20

A framework to capture potential impacts of *dynamic* disruptions of a disaster, especially on collective human behaviors to assess a community's resilience to wildfires in space and time.



1) Which community is more resilience compared to others and why?
2) Did a community bounce back to its original status after a certain time or form a new normalcy?
3) What are the similarities and differences among communities?

Scale up the concept of resilience to a more empirical framework that can be quantified and visualized.

Data Collection

- Mobility data
- Census data

DTW Clustering

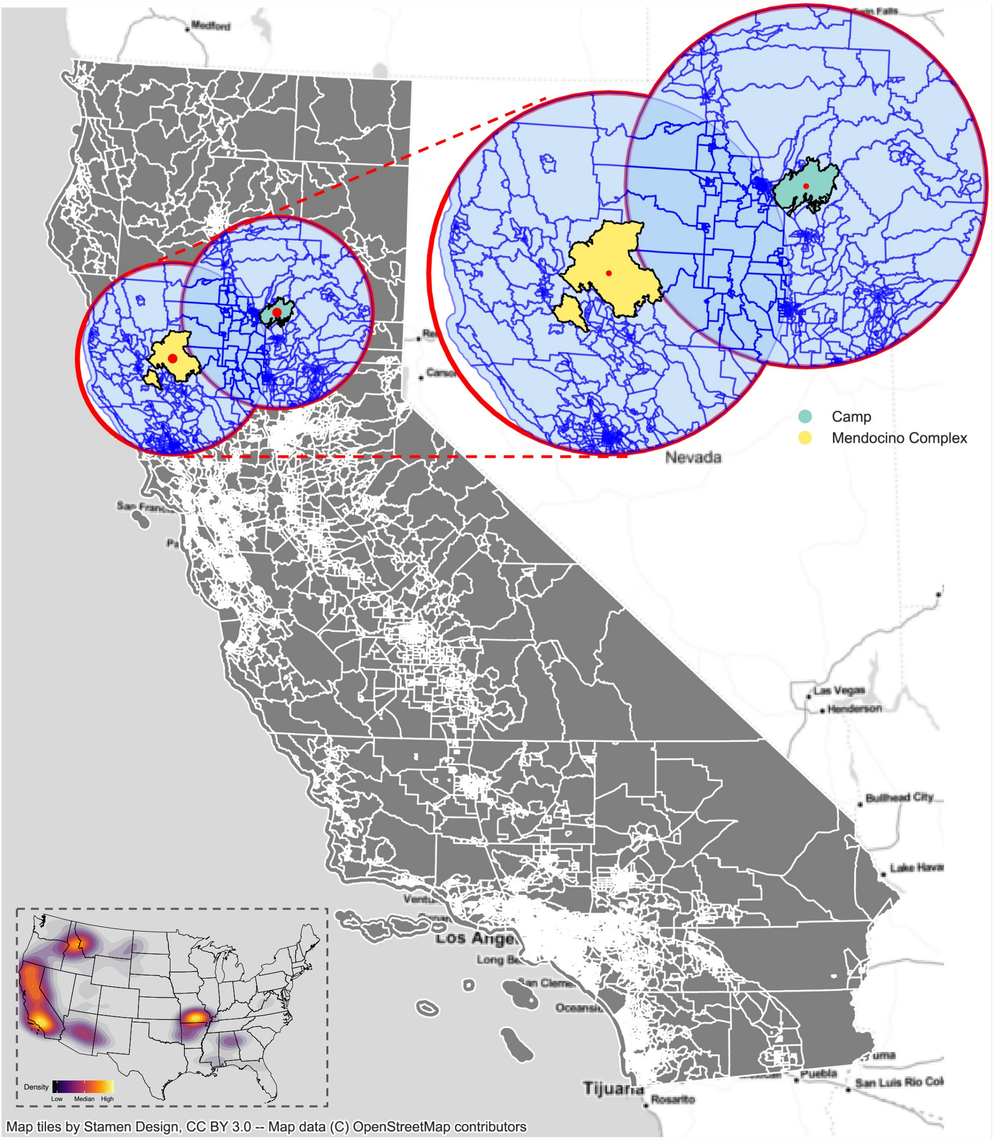
- DTW Distance
- Similarity measurement

Resilience Triangle Detection

- Network construction
- Degree centrality analysis
- Triangle detection

Regression analysis

- Demographic information
- Socio-economic status
- Built environment



- **California**: the most populous state in the US - ranks as the most wildfire-prone state in the country
- **Two wildfires**:

Wildfire Name	Start Date	End Date	Description
Mendocino Complex	08/27/2018	01/04/2019	The largest wildfire to date with records back to 1933, which has burned over 450k acres.
Camp	11/8/2018	11/25/2018	The costliest and deadliest wildfire, which has destroyed more than 18,500 buildings.

- **Data:**
  - SafeGraph: Jan 2018 - Dec 2019
- **Analysis unit**: Census Block Group (CBG)
- **Time interval**: Month

WORKFLOW

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A Framework to Quantitatively Assess and Enhance the Seismic Resilience of Communities

Michel Bruneau,[a) M.EERI] Stephanie E. Chang,[b) M.EERI] Ronald T. Eguchi,[c) M.EERI] George C. Lee,[a) M.EERI] Thomas D. O'Rourke,[d) M.EERI] Andrei M. Reinhorn,[e) M.EERI] Masanobu Shinozuka,[f)] Kathleen Tierney,[g) M.EERI] William A. Wallace,[h)] and Detlof von Winterfeldt[i)]

The co-authors of this paper are listed in alphabetical order.

This paper presents a conceptual framework to define seismic resilience of communities and quantitative measures of resilience that can be useful for a coordinated research effort focusing on enhancing this resilience. This framework relies on the complementary measures of resilience: "Reduced failure probabilities," "Reduced consequences from failures," and "Reduced time to recovery." The framework also includes quantitative measures of the "ends" of robustness and rapidity, and the "means" of resourcefulness and redundancy, and integrates those measures into the four dimensions of community resilience—technical, organizational, social, and economic—all of which can be used to quantify measures of resilience for various types of physical and organizational systems. Systems diagrams then establish the tasks required to achieve these objectives. This framework can be useful in future research to determine the resiliency of different units of analysis and systems, and to develop resiliency targets and detailed analytical procedures to generate these values. [DOI: 10.1193/1.1623497]

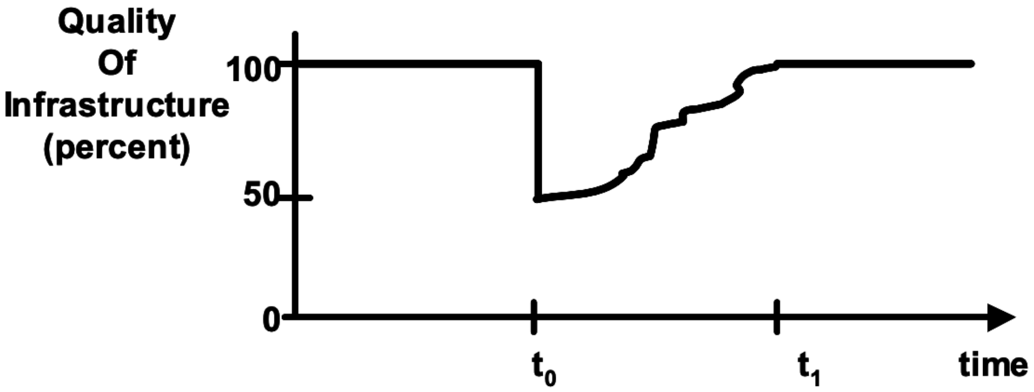
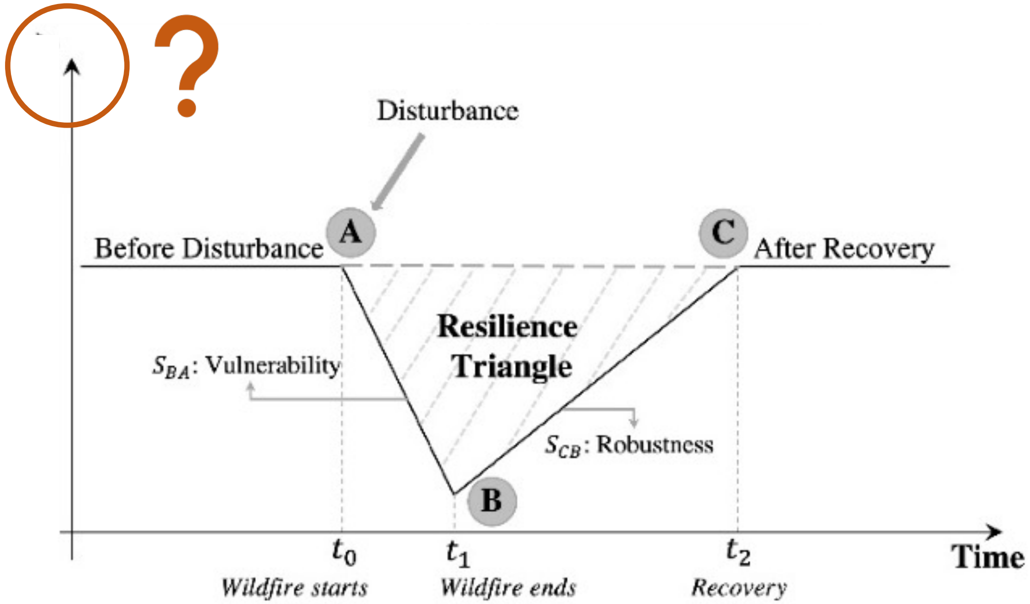
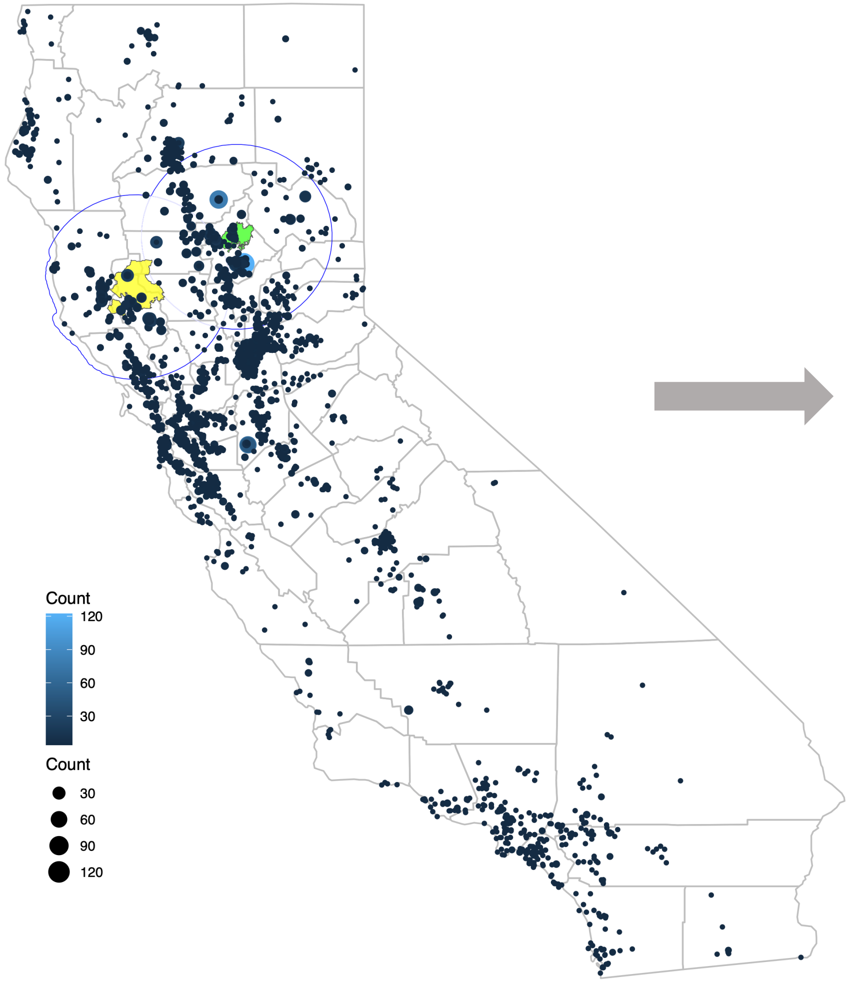
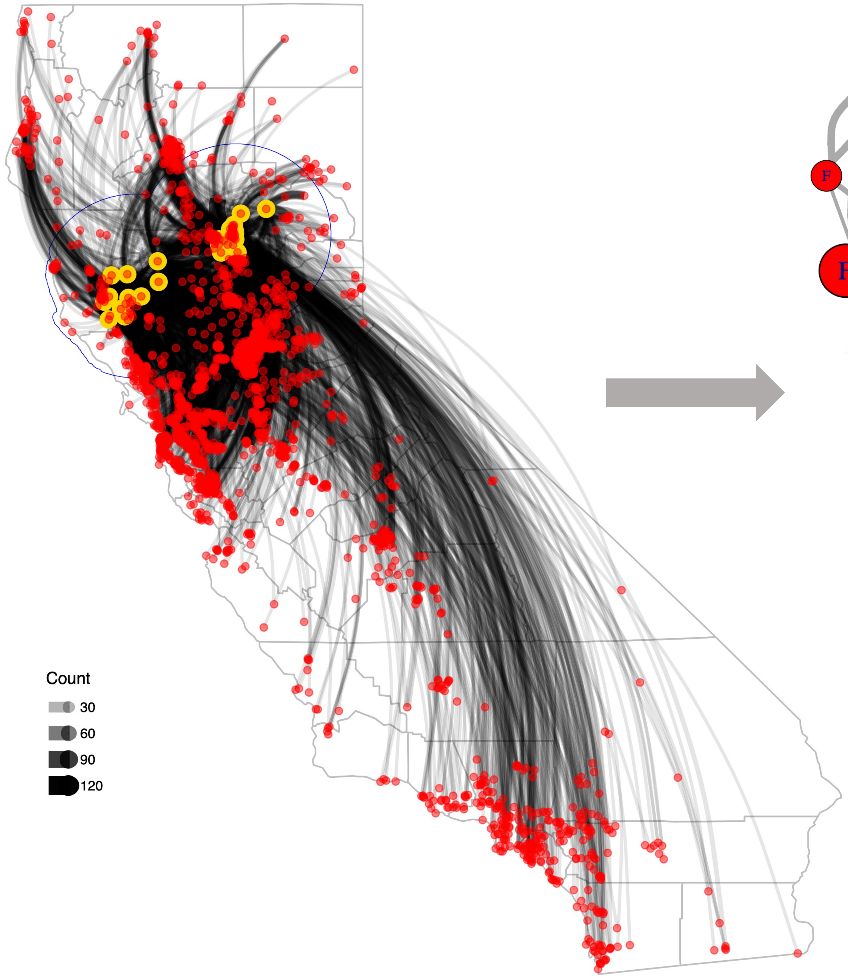


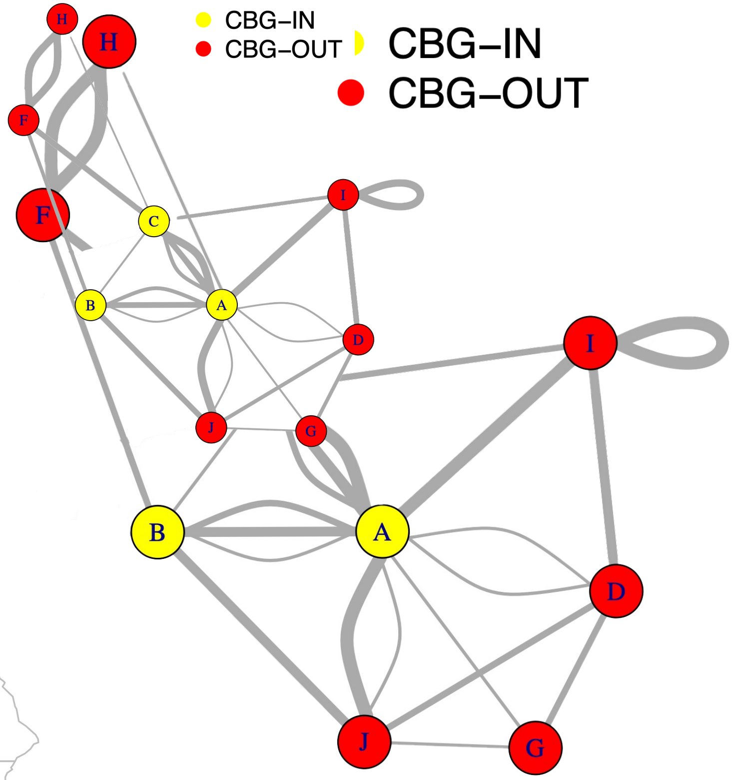
Figure 1. Schematic representation of seismic resilience concept (Bruneau et al. 2003)



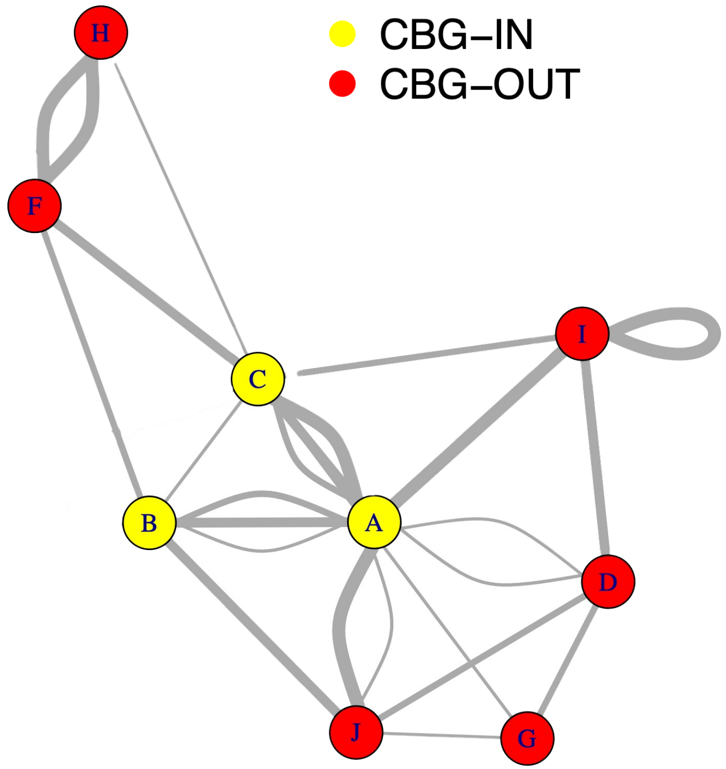
Bruneau, M., Chang, S.E., Eguchi, R.T., Lee, G.C., O'Rourke, T.D., Reinhorn, A.M., Shinozuka, M., Tierney, K., Wallace, W.A., von Winterfeldt, D., 2003. A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake Spectra 19, 733–752. doi:10.1193/1.1623497. publisher: SAGE Publications Ltd STM.







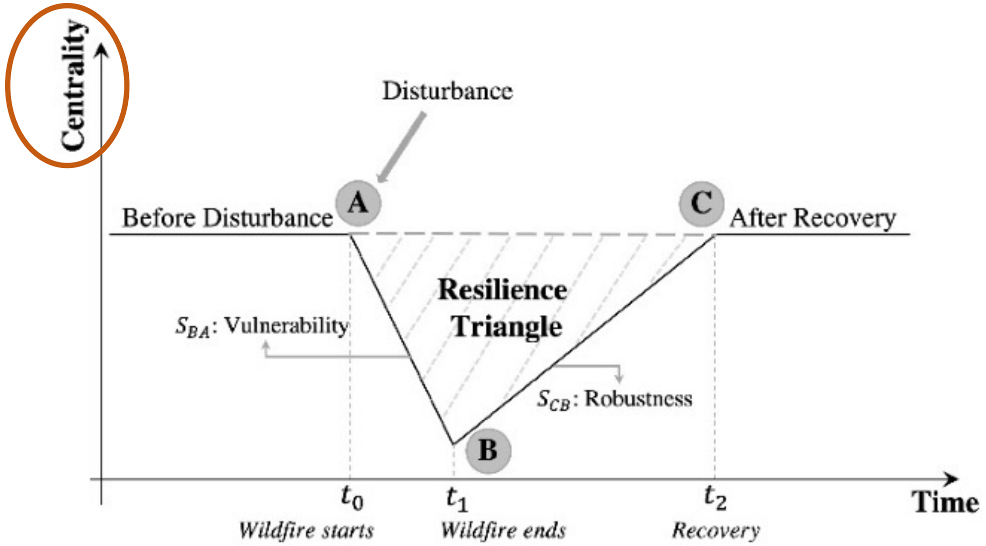
Sharifi, A., 2019. Resilient urban forms: A review of literature on streets and street networks. Building and Environment 147, 171–187.



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 (Sharif., 2019)



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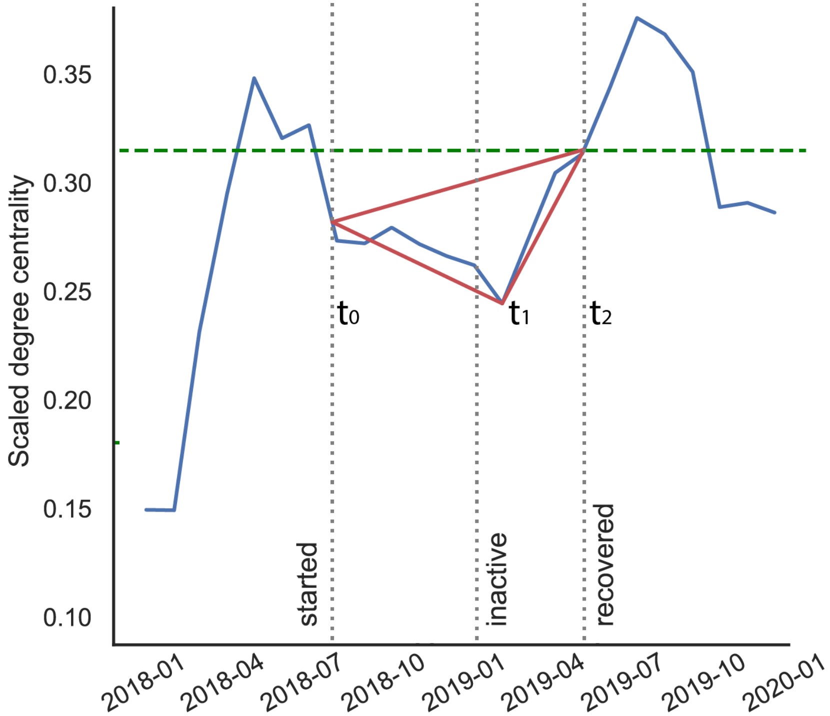

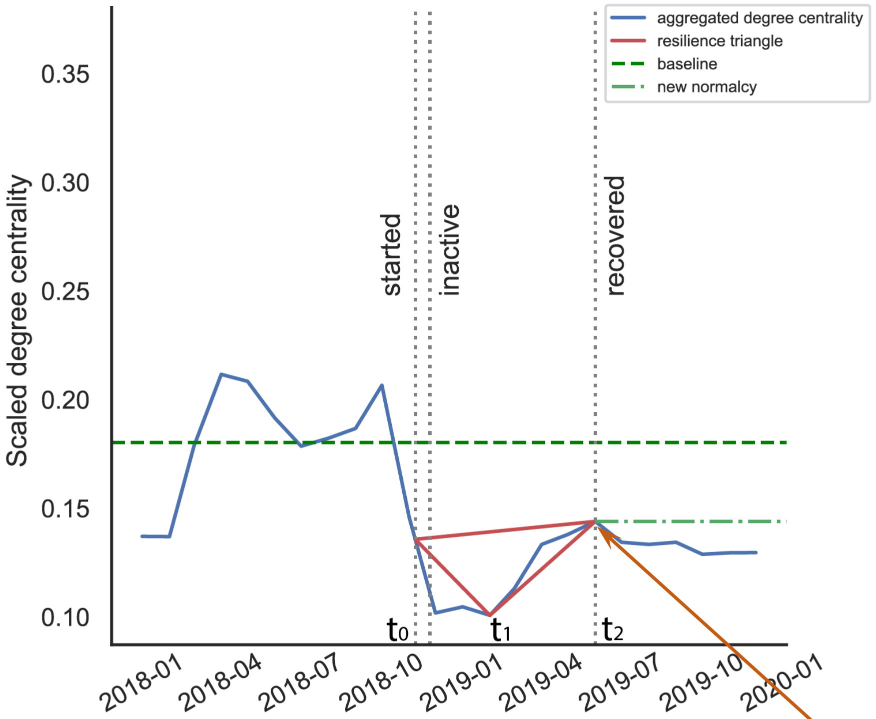

$\boldsymbol{t_0}$: the onset of a disaster

$\boldsymbol{t_1}$: the time when degree centrality reaches its minimum value between t_0 and t_2

$\boldsymbol{t_2}$: the time when the degree centrality fully bounces back to the pre-wildfire baseline level

$\boldsymbol{t_2}$: the time when the maximum degree centrality occurs after the wildfire becomes inactive

New normalcy

The resilience triangle records the *abrupt losses* in performance of a social unit (i.e., CBG) under the disruption of a disaster.

- **Depth**: the severity of the disruption
- **Length**: the recovery time
- **Area**: the resilience of the social unit.

The smaller the area is, the more resilient the social unit is.

WORKFLOW

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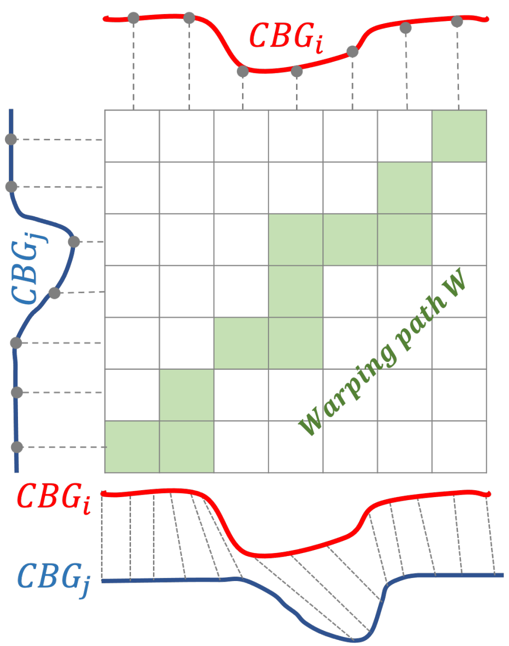
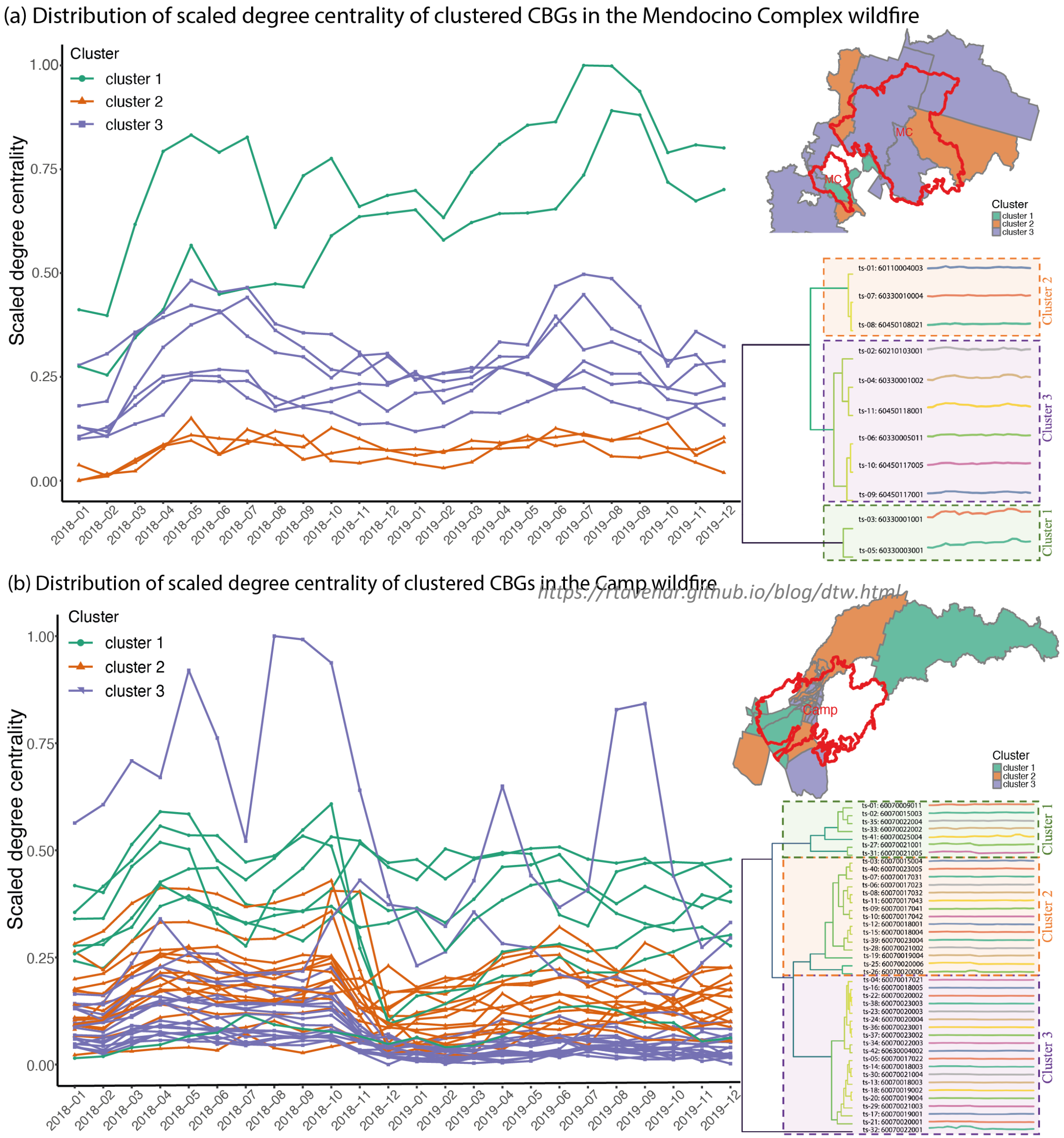
Dynamic Time Warping Clustering



Similarity measurement

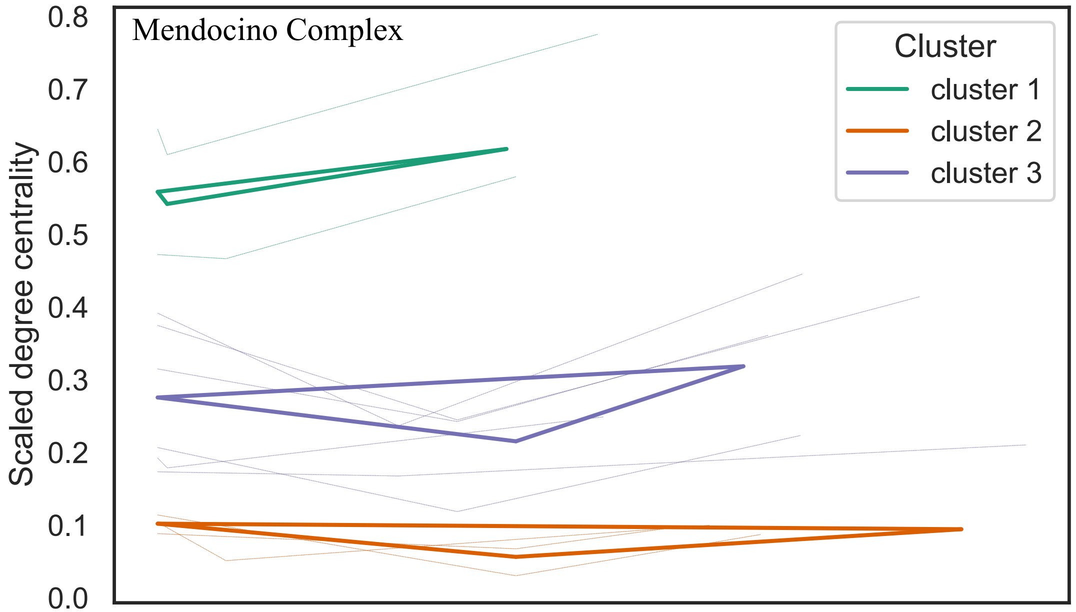
- DTW clustering: an accurate method for clustering time series data (Wang et al., 2013)
- Warping path: identifies the optimum matching (i.e., to minimize distance) between two sequences using a dynamic programming approach (Zhang et al., 2017)

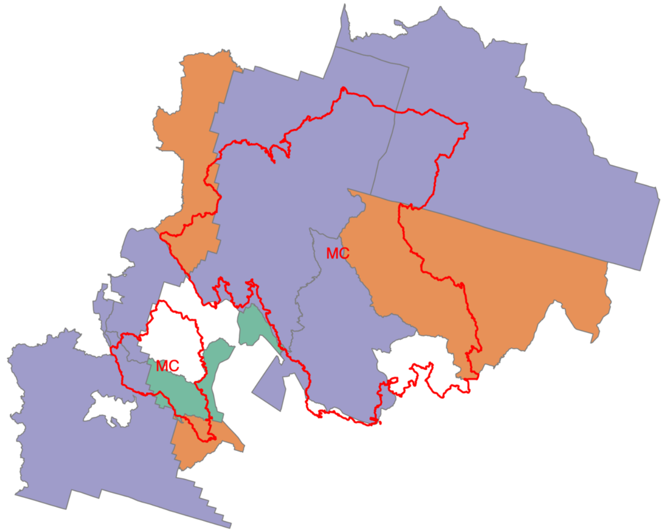


- Each CBG can have a different response and recovery pattern of degree centrality
- Classify CBGs based on changing patterns of degree centrality to evaluate the similarity

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
Zhang, Z., Tavenard, R., Bailly, A., Tang, X., Tang, P., Corpetti, T., 2017. Dynamic time warping under limited warping path length. Information Sciences 393, 91–107

CLASSIFIED RESILIENCE TRIANGLE



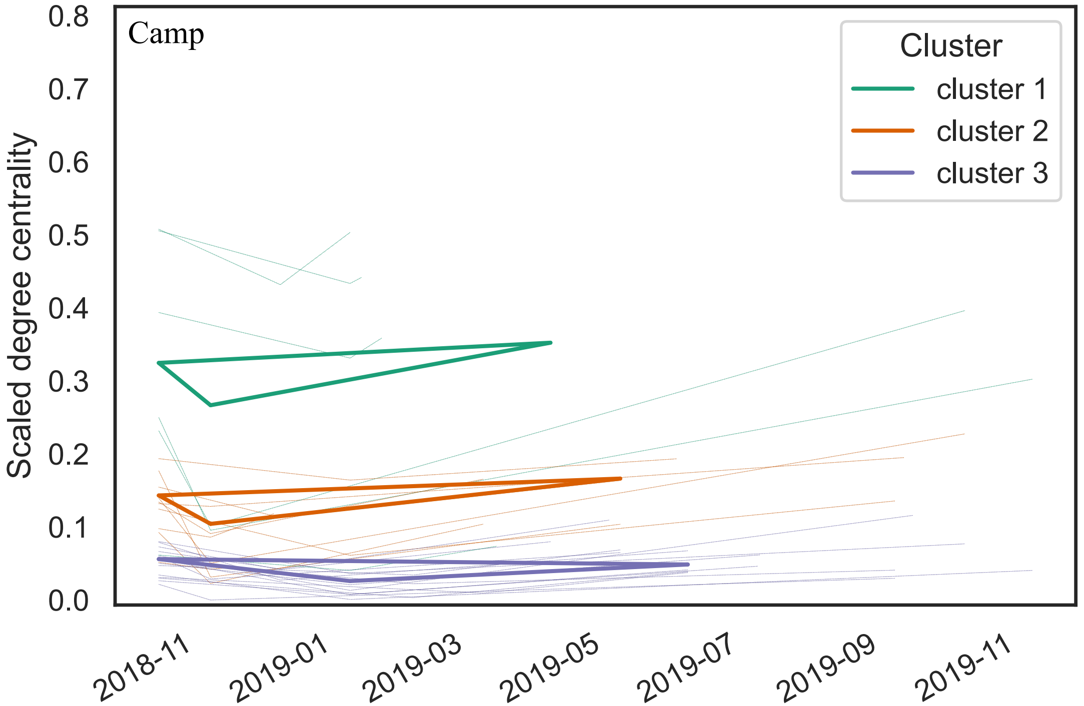


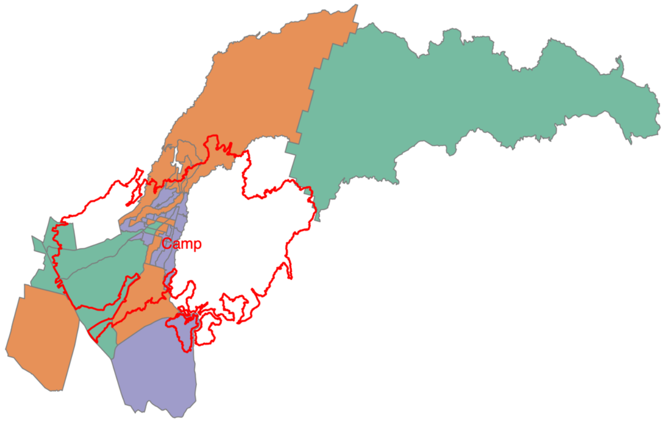
Cluster 1

Cluster 2

Cluster 3

Resilience





Cluster 3

Cluster 2

Cluster 1

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Demographic information

Socio-economic status

Built environment characteristics

Table 1: Description of independent variables

Independent Variable	Description
AvgDistance	Average distance from home CBGs to a target CBG
%PopDist<3km	Percentage of population travel within 3 km from home CBGs to a target CBG
AreaInWildfire	The area of a target CBG within the wildfire area
# of Housing Units	Number of housing units of a target CBG
Med Household Income	Median household income of a target CBG
MedAgeMale	Median age of male of a target CBG
MedAgeFemale	Median age of female of a target CBG
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% Pop >Undergraduate	The percentage of people that are undergraduate or higher of a target CBG

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Table 2: Statistical summary of regression models for the two wildfires

	Dependent variable: Degree Centrality	
	Mendocino Complex	Camp
(Intercept)	7.8055***(0.4516)	6.2647***(0.1613)
AvgDistance	0.0000*(0.0000)	−0.0000(0.0000)
%PopDist<3km	−0.0137***(0.0024)	0.0104***(0.0009)
%AreaInWildfire	−0.0000**(0.0000)	0.0000***(0.0000)
# of Housing Units	0.0017***(0.0005)	0.0022***(0.0002)
Med Household Income	0.0000(0.0000)	0.0000***(0.0000)
MedAgeMale	−0.0013(0.0025)	−0.0060**(0.0019)
MedAgeFemale	−0.0311**(0.0094)	−0.0125***(0.0021)
# of workers	−0.0019(0.0012)	−0.0025***(0.0003)
% Pop >Undergraduate	0.0259(0.0210)	−0.0239***(0.0043)
cluster 2	−1.3039***(0.0928)	−0.6918***(0.0653)
cluster 3	−0.6181***(0.0785)	−1.1131***(0.0674)
R^2	0.8837	0.5884
Adj. R^2	0.8787	0.5832
Num. obs.	288	950

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

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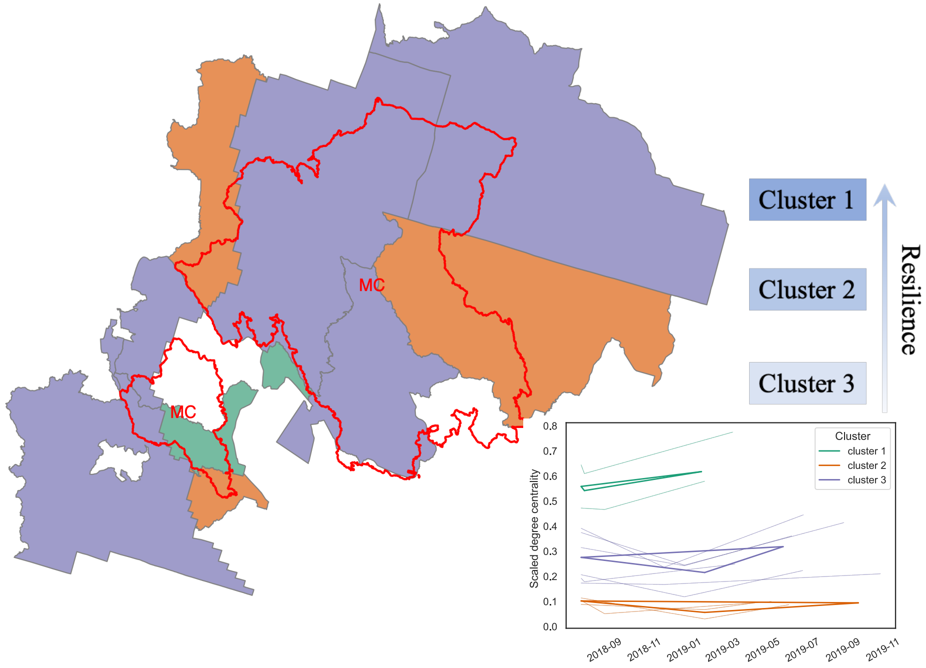
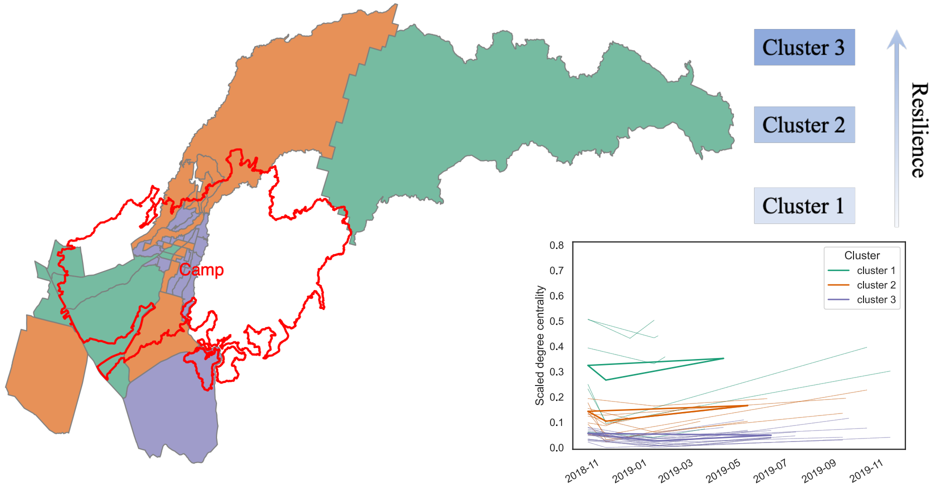
Table 3: Statistical summary of different factors for the two wildfires

Cluster 1	N		Mean		St. Dev.		Min		Max	
	MC	Camp	MC	Camp	MC	Camp	MC	Camp	MC	Camp
Average Distance (km)	48	168	108.293	59.584	23.705	25.164	49.634	15.132	157.065	176.266
% Population within 3km	48	168	38.454	33.528	6.088	13.510	24.054	6.993	48.921	63.515
Area within Wildfire (km^2)	48	168	27.083	16.885	26.847	24.727	0.517	0.791	53.649	71.604
# of Housing Units	48	168	634.500	700.143	63.161	188.709	572	437	697	1,099
Median Household Income	48	120	50.130	55.666	4.493	18.078	45.684	38.917	54.575	90.156
Median Age (Male)	48	168	37.700	43.457	3.436	3.545	34.300	38.400	41.100	48.800
Median Age (Female)	48	168	39.450	45.400	0.152	7.748	39.300	33.900	39.600	59.100
# of Full-time Workers	48	168	347.000	364.857	2.021	233.517	345	113	349	835
% Education >Undergraduate	48	168	4.393	6.444	1.848	2.902	2.564	2.291	6.222	9.288
Cluster 2	**N**		**Mean**		**St. Dev.**		**Min**		**Max**	
	MC	Camp	MC	Camp	MC	Camp	MC	Camp	MC	Camp
Average Distance (km)	72	360	80.153	54.779	33.502	21.108	22.420	10.300	185.619	153.289
% Population within 3km	72	360	44.528	46.371	12.382	20.022	16.406	2.469	64.286	80.000
Area within Wildfire (km^2)	72	360	122.393	5.617	124.615	8.359	11.132	0.006	295.008	30.579
# of Housing Units	72	360	372.000	543.067	14.823	227.980	357	303	392	1,037
Median Household Income	72	360	60.166	48.675	26.471	13.873	38.542	24.565	97.165	73.194
Median Age (Male)	72	360	45.333	44.287	9.850	9.533	32.900	26.500	56.800	58.800
Median Age (Female)	72	360	44.033	45.393	10.362	11.226	31.300	24.900	56.500	59.400
# of Full-time Workers	72	360	196.667	287.133	120.218	156.896	78	107	360	715
% Education >Undergraduate	72	360	3.455	6.947	1.938	4.749	0.733	0.000	4.843	16.667
Cluster 3	**N**		**Mean**		**St. Dev.**		**Min**		**Max**	
	MC	Camp	MC	Camp	MC	Camp	MC	Camp	MC	Camp
Average Distance (km)	168	470	89.281	50.112	40.419	24.681	23.355	6.355	202.424	152.443
% Population within 3km	168	470	45.462	39.990	14.947	22.724	16.354	2.010	72.704	91.209
Area within Wildfire (km^2)	168	470	178.212	2.934	244.604	2.561	0.018	0.745	702.816	11.928
# of Housing Units	168	470	533.429	473.370	243.628	165.208	248	170	1,034	928
Median Household Income	168	470	58.407	55.593	20.280	16.947	26.250	25.469	81.875	96.844
Median Age (Male)	168	470	44.386	50.734	10.077	12.270	26.800	20.700	56.900	64.300
Median Age (Female)	168	470	45.771	52.907	7.523	11.744	34.900	27.700	69.100	53.600
# of Full-time Workers	168	470	209.429	226.309	49.965	65.624	117	87	259	360
% Education >Undergraduate	168	470	6.524	6.495	3.563	4.855	1.370	0.000	11.711	15.909



Mendocino Complex

- 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



Camp

- 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; relatively 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

In summary:

- Quantifying community resilience is an open research challenge
- Develops a novel framework to quantify resilience after a disaster based on network analysis and human mobility data combined with the concept of resilience triangle
- Results show community resilience is highly related to socio-economic & built environmental characteristics of the affected areas
- The study paves a way to study disasters & their long-term impacts on society

Resilience

Acknowledgement

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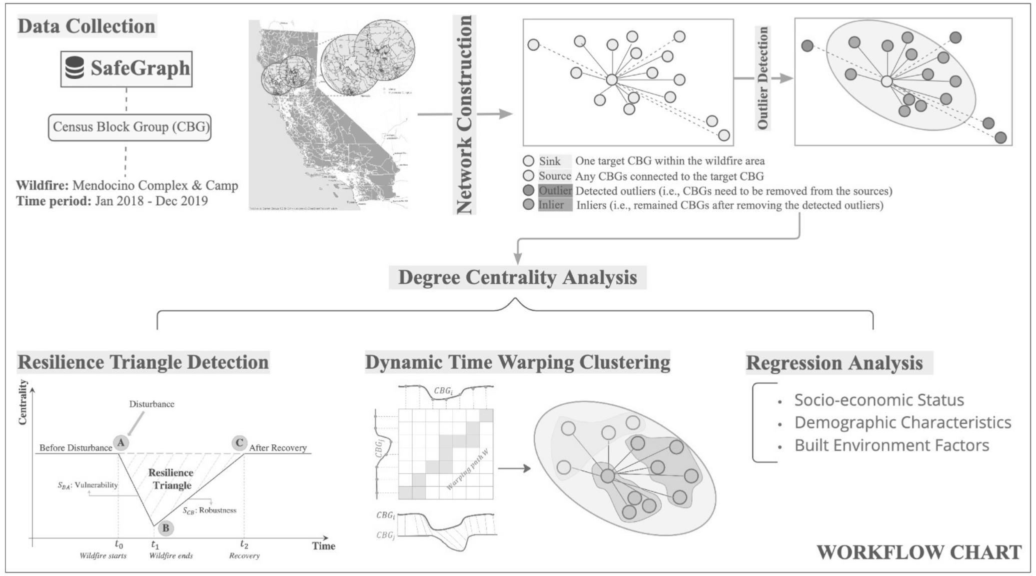
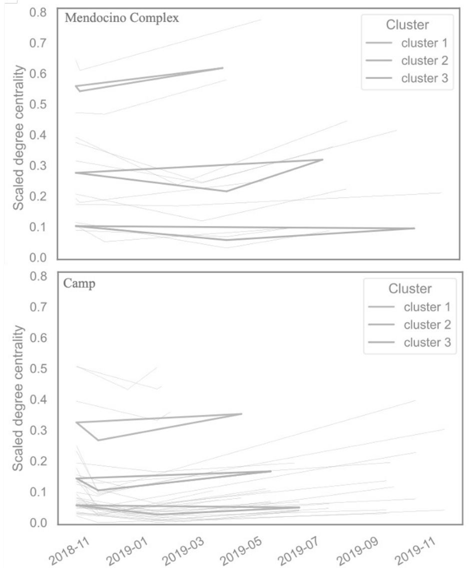
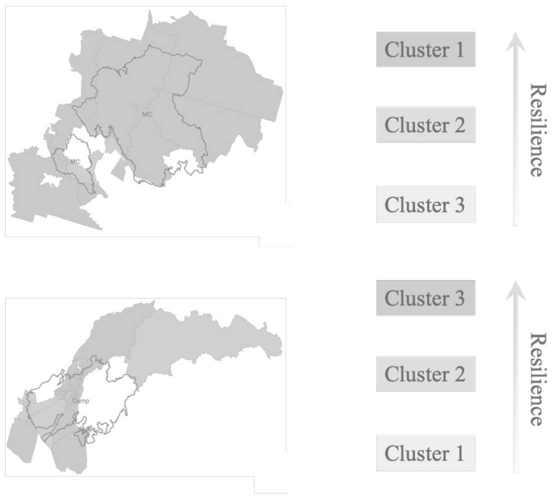
University at Buffalo







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