Modeling Wildfire Evacuation with Embedded Fuzzy Cognitive Maps:

An Agent-Based Simulation of Emotion and Social Contagion

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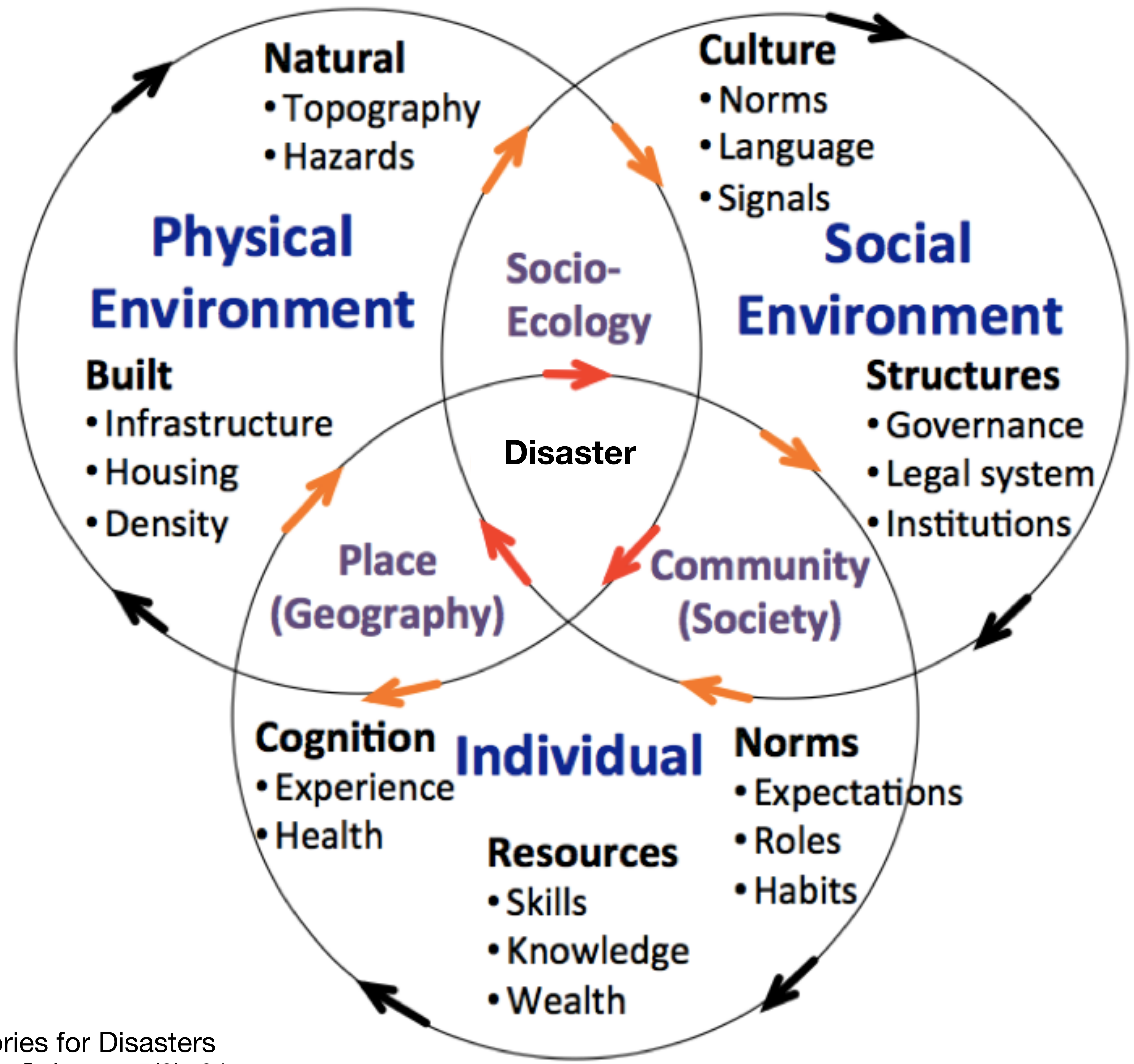
Talk Outline

- Motivation and Introduction
- Case Study
- Model Methodology
- Results
- Summary and Outlook

Motivation: Interacting Systems For Disasters



Burger, Kennedy & Crooks, (2021), Organizing Theories for Disasters into a Complex Adaptive System Framework, Urban Science, 5(3), 61.

Introduction

- Wildfires occur frequently worldwide, causing increasingly both casualties and property losses.

- Faced with the combined impact of multiple risk factors such as **climate change**, and the expansion of **wildland-urban interfaces (WUI)**, improving people's response capabilities and evacuation efficiency during such extreme events has become an urgent and complex challenge.

- For example in the US, **60,000 communities are at risk of WUI fires**.

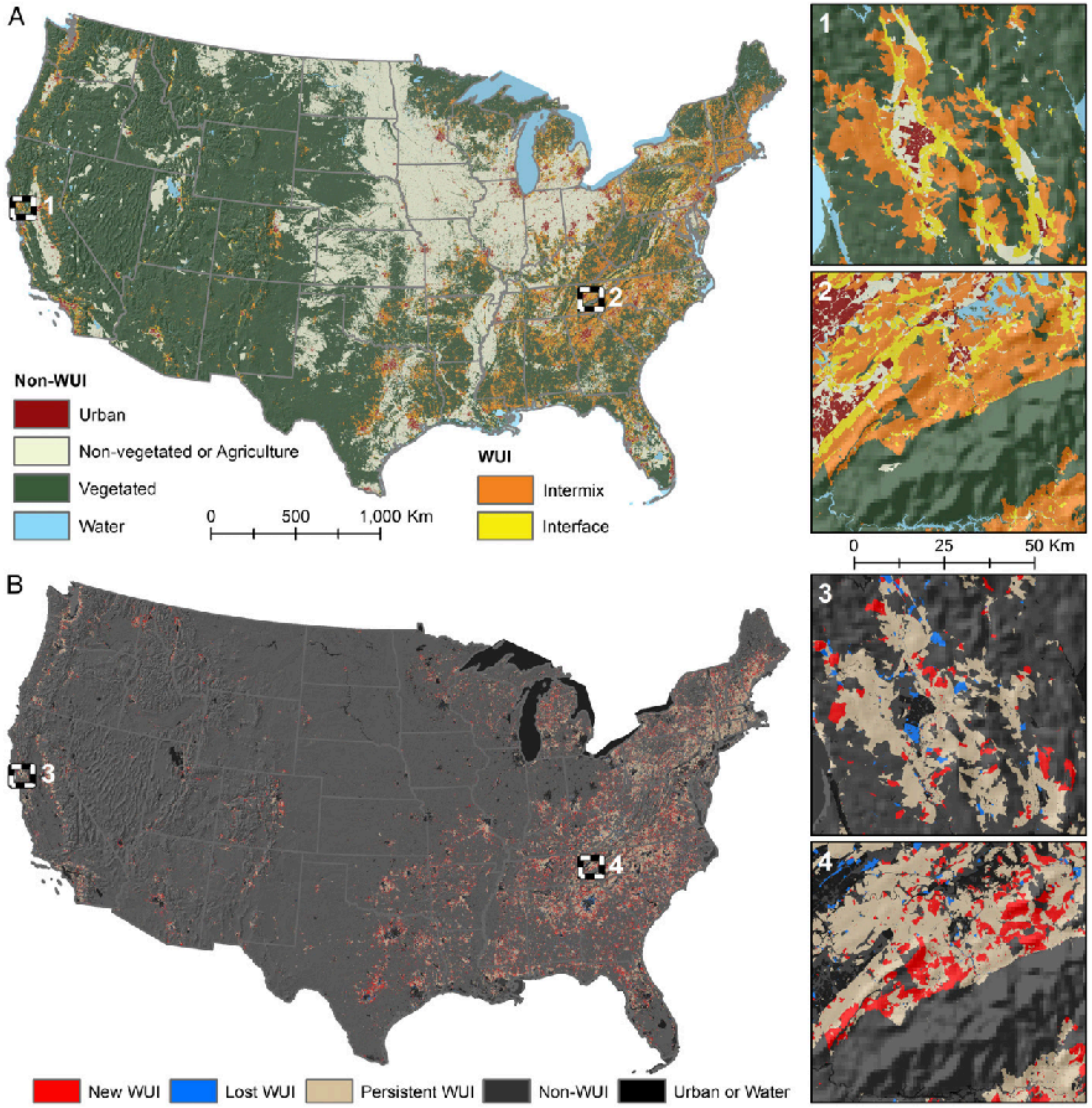
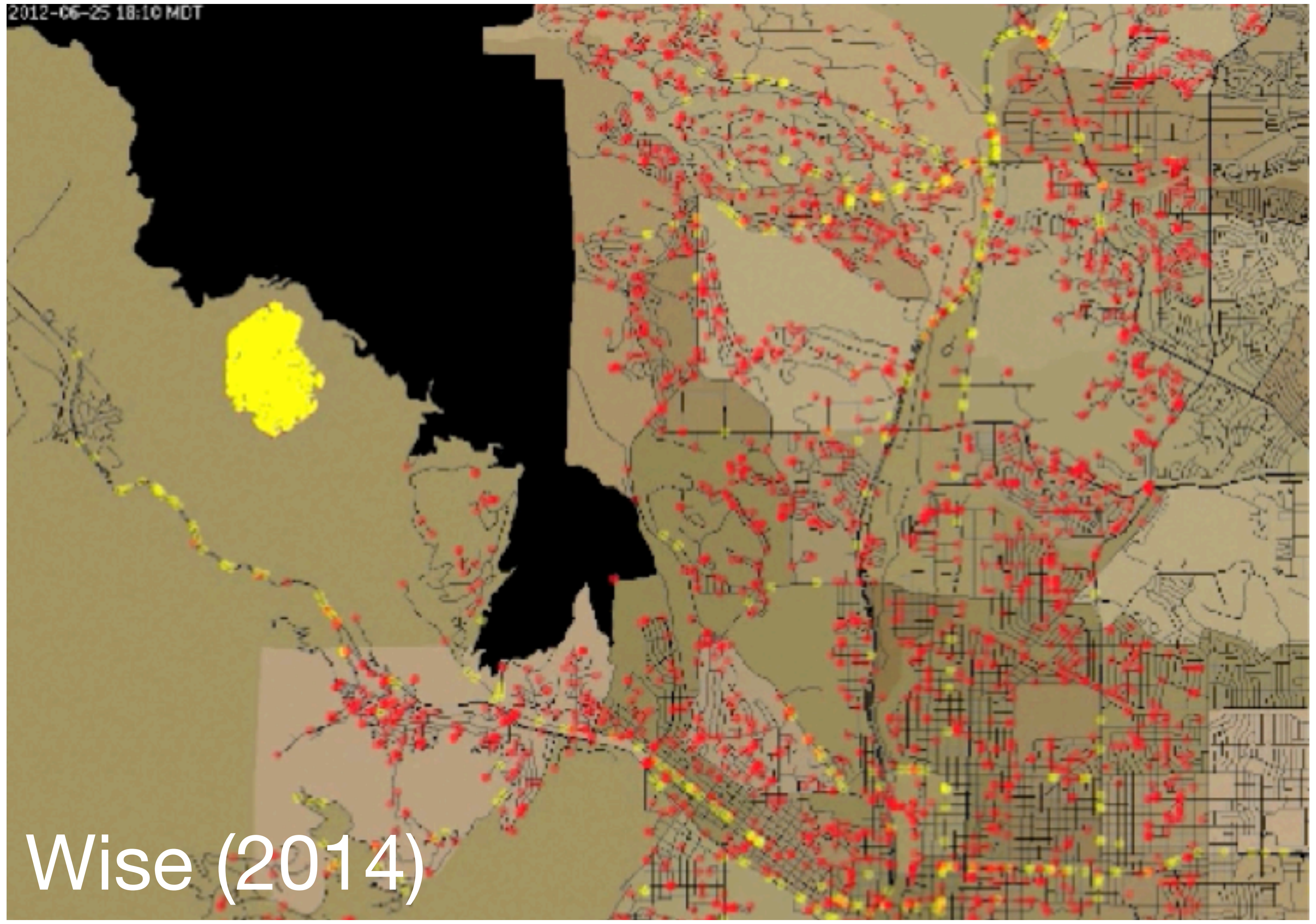


Fig. 1. The WUI in the United States was widespread in 2010 (*A*), as were changes in WUI area (*B*), for example, in and around Santa Rosa, California (1, 3), and Gatlinburg, Tennessee (2, 4), areas where wildfires destroyed many homes in 2017 and 2016, respectively.

Source: Radeloff et al., 2018. Rapid growth of the US wildland-urban interface raises wildfire risk. *Proceedings of the National Academy of Sciences*, 115(13), pp.3314-3319.

Background

- Traditional models of wildfire evacuation typically only considered people or vehicles as flows
  - e.g., Vandaele *et al*., (2000) studied a traffic flow model based on queueing theory.
- **Growing interest in ABM** for disaster evacuation research
- However, many ABMs of wildfire evacuation are based on the **rational choice assumption**.
- Studies have shown that the **emotions** (e.g., panic) significantly affect an individuals' judgment and behavioral choices.
- While the influence of psychological factors can be revealed in post-event surveys, there is a lack of modeling methods that can dynamically demonstrate the impact of emotions in ABM during emergency evacuations (Trivedi & Rao 2018).



Vandaele *et al.*,: A queueing based traffic flow model. Transportation Research Part D: Transport and Environment 5(2), 121–135 (2000

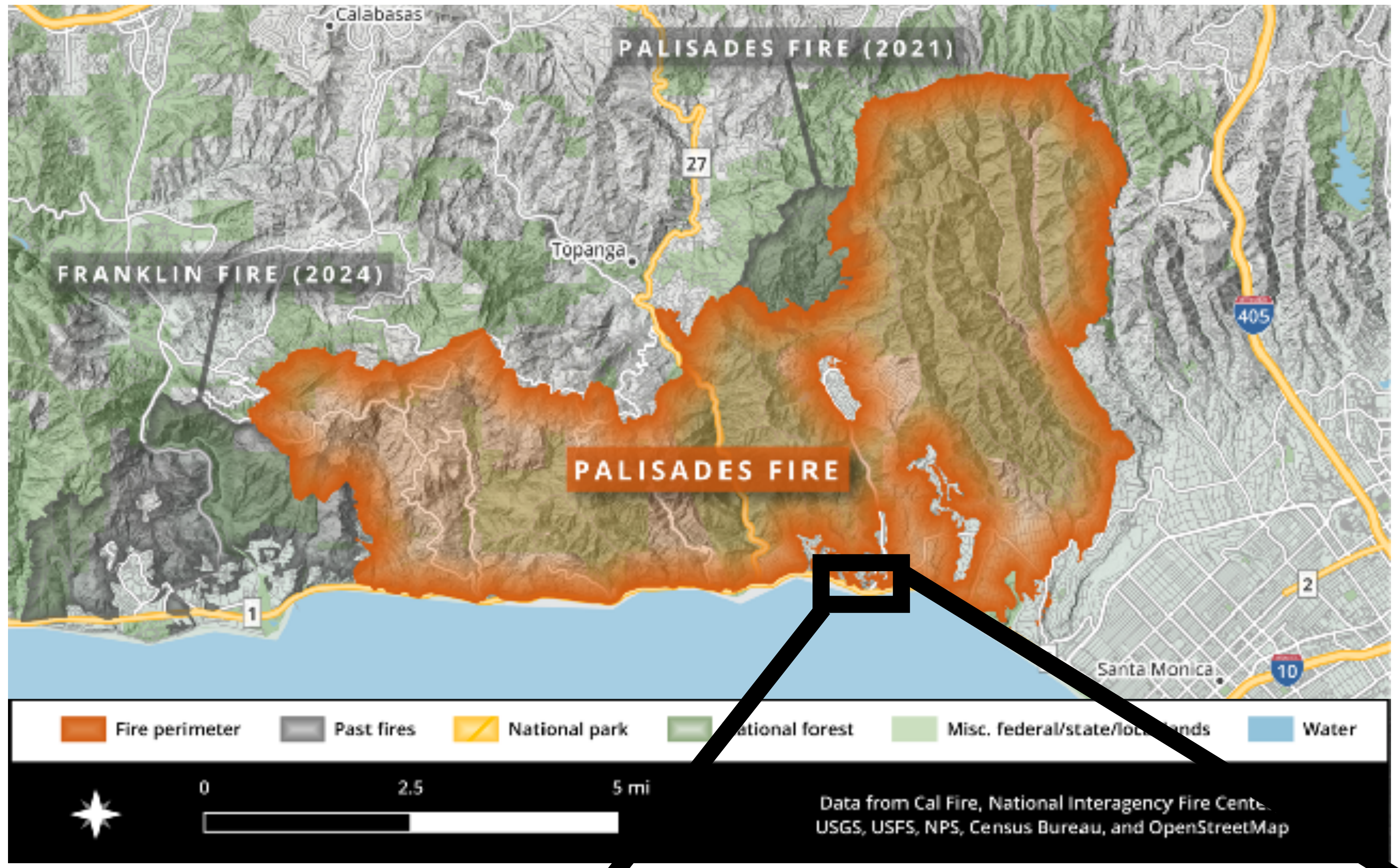
Trivedi and Rao: Agent-based modeling of emergency evacuations considering human panic behavior. *IEEE Transactions on Computational Social Systems* 5(1), 277–288 (2018)

Wise, S. (2014), *Using Social Media Content To Inform Agent-based Models For Humanitarian Crisis Response*, PhD Dissertation, George Mason University, Fairfax, VA.

The Model

Study Area

- Simulation area is located in the Castellammare neighborhood of the Pacific Palisades, in western Los Angeles, California
- The area was damaged by the 2025 Los Angeles fires.
- The area has a composite “coast-hill-city topography” which is an ideal scenario for researching the interaction between coastline constraints, road bottlenecks, and fire.



https://en.wikipedia.org/wiki/Palisades_Fire

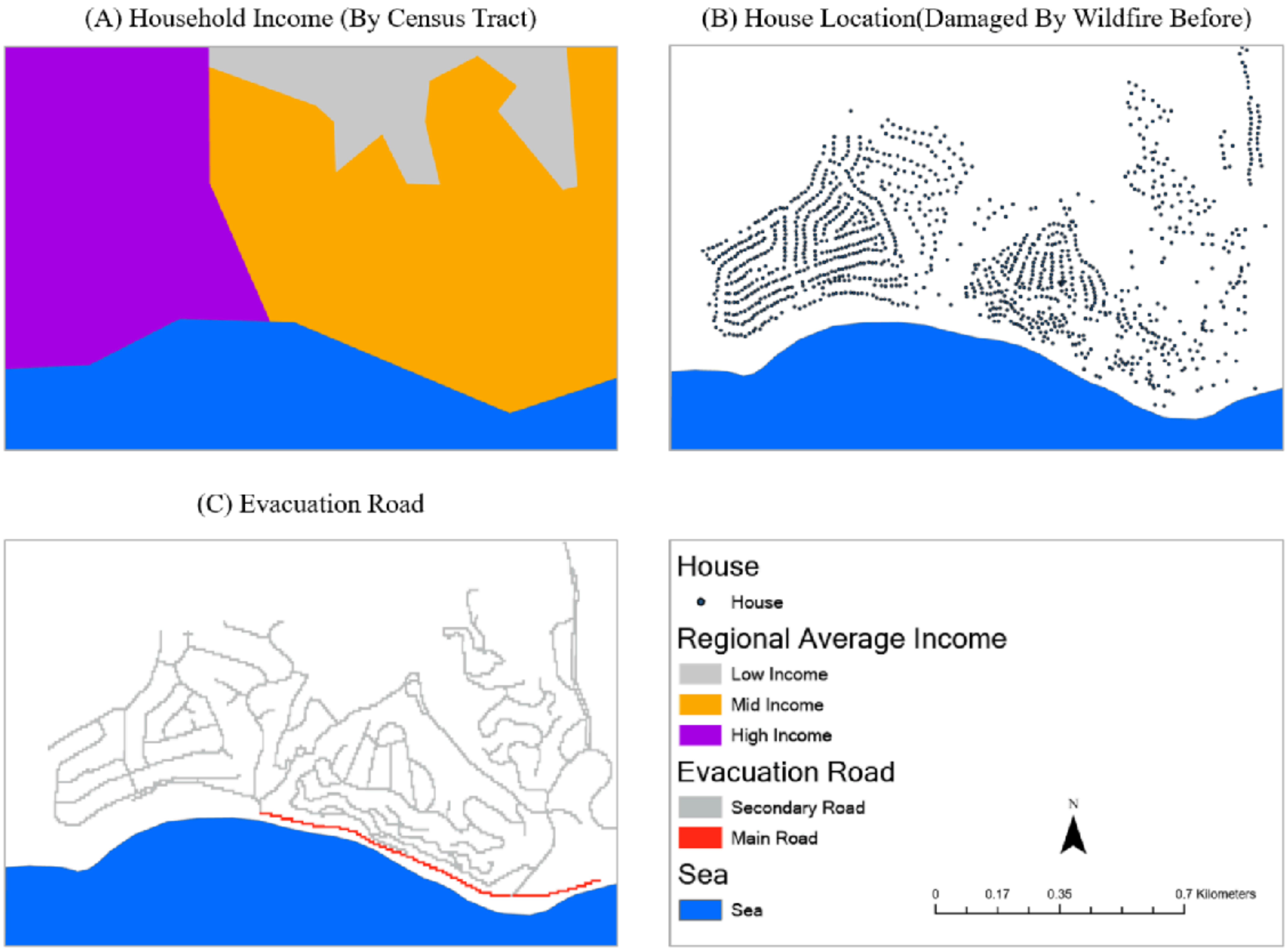
Find Out More

Study area: A wildfire-affected community in Los Angeles in 2025

Data Layers

Table 1. Input Data Sources

Data	Details	Resolution	Type
Household income	By the Los Angeles County Department of Public Health	By Census Tract	.shp
Household location	DINS by CAL FIRE	Point	.csv
Street Data	Street Inventory by StreetsLA	10m by 10m	.asc



Data used in the setting up the model experiment. (A) is household income data, (B) is location of previously affected houses, and (C) is evacuation road data.

Process Overview and Scheduling

- The model comprises three main entities: **evacuees**, **responders**, and **environmental grid cells** (i.e., patches) and the time step is 1 second.

- Each iteration sequentially executes **four phases**.

1. The model expands the burning area based on the fire propagation speed and dynamically sets road pass-ability.
    - Normal average speed of California fire in a light breeze, which is 2 km/h.

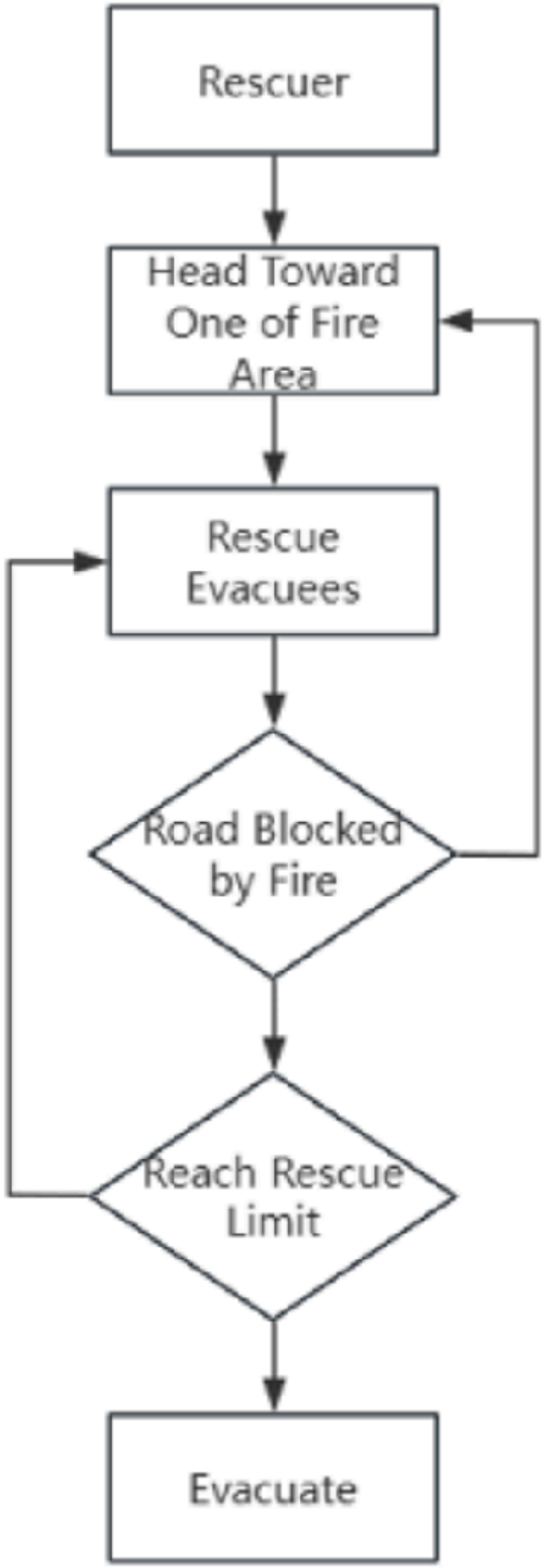
2. Calculates and updates the emotions and behaviors of evacuees.

3. Schedules the search-rescue-evacuation process for responders.

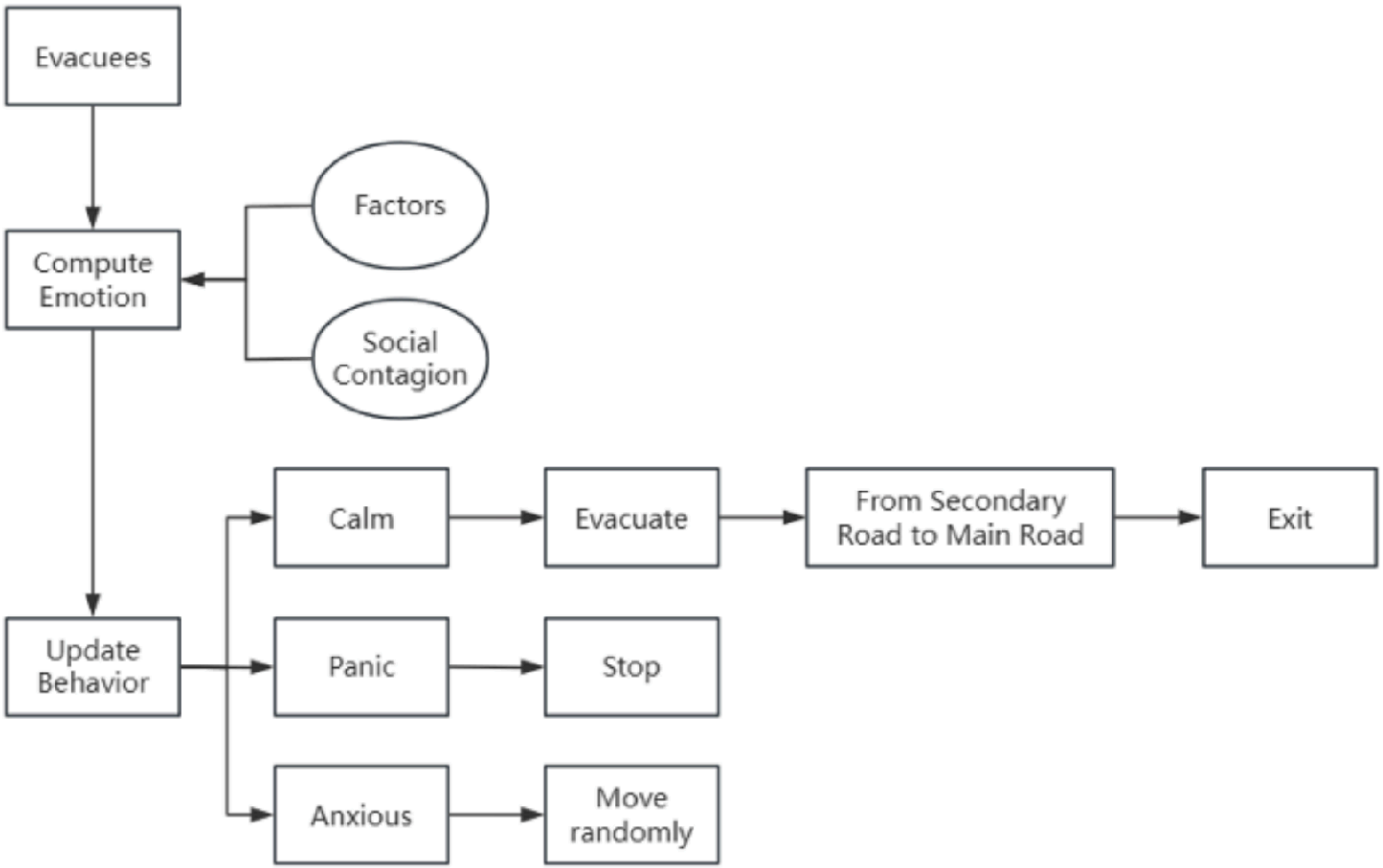
4. Statistics are recorded, and termination conditions are triggered (i.e., all individuals safely evacuated, or 10,000 ticks reached).

Rescuer Agents

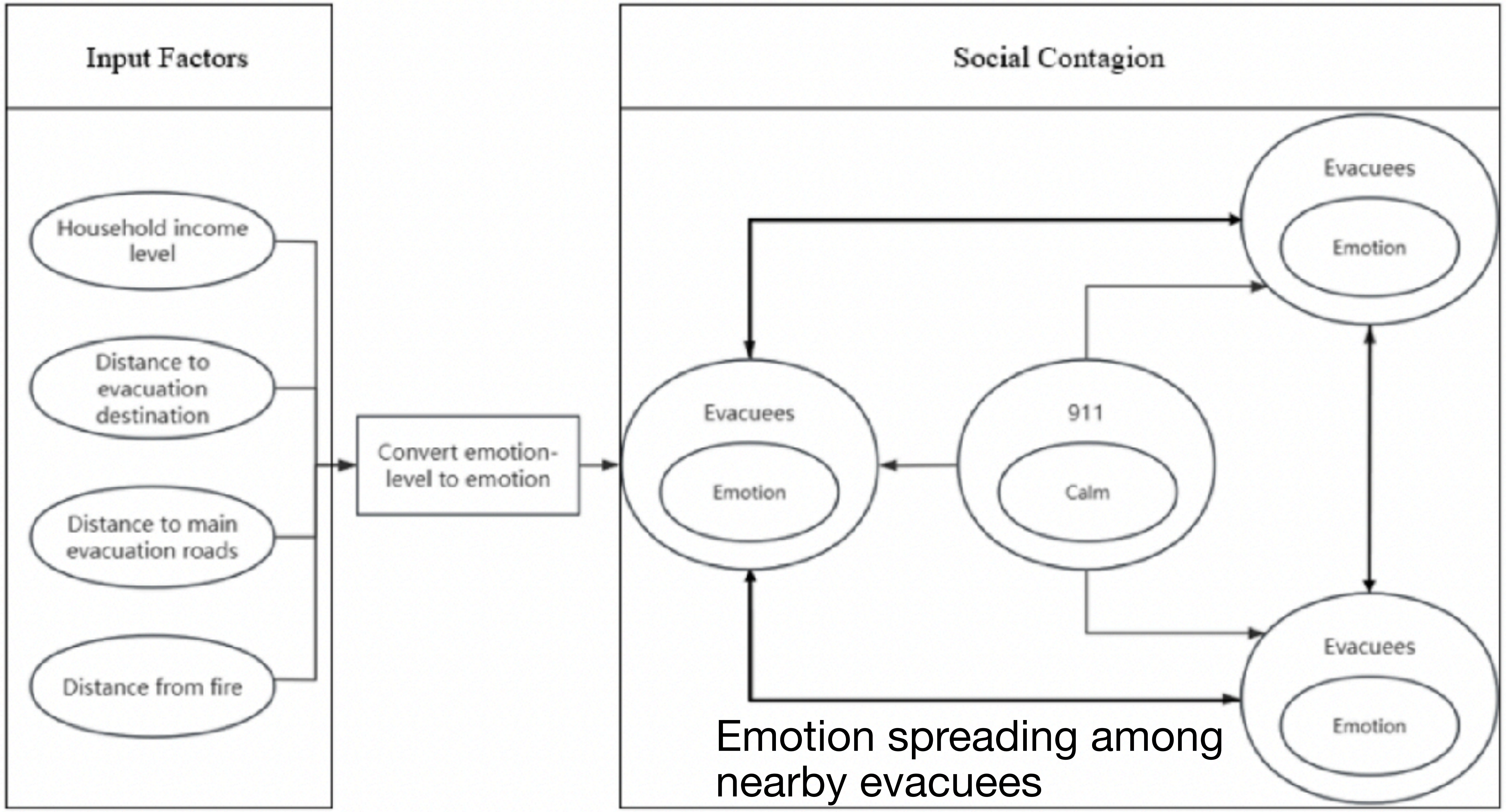
- First they “***Head Toward Fire Area***” using A* pathfinding to navigate.
  - If they encounter a road blocked by new fire, they immediately replan their route.
- During this forward movement, rescuers perform “**Rescue Evacuees**”.
  - They scan for evacuees within an 8-patch radius, pick them up until reaching the transport capacity limit (default 5 people).
- At each tick, rescuers check road conditions (e.g., **Road Blocked by Fire**).
  - If the next segment suddenly catches fire, the rescuer returns to step 1 to select a new location.
  - At the same time, the number of evacuees on board is checked (**Reach Rescue Limit**). Once the capacity limit is reached, rescuers switch to “**evacuation mode**”.
    - Takes the fastest route to the exit.



Evacuees’ Workflow



Agent-level Embedded FCM loop with Social Contagion



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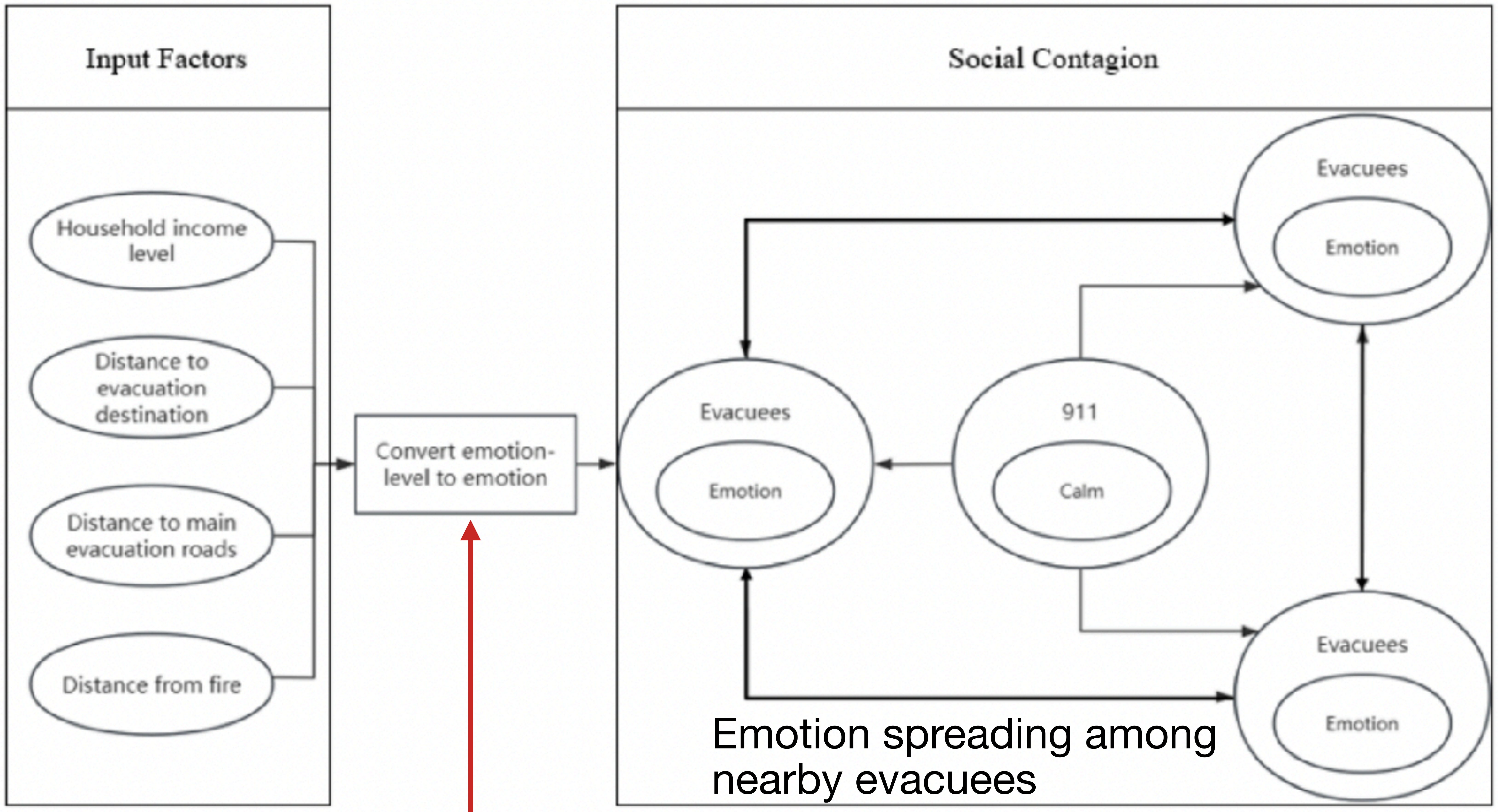
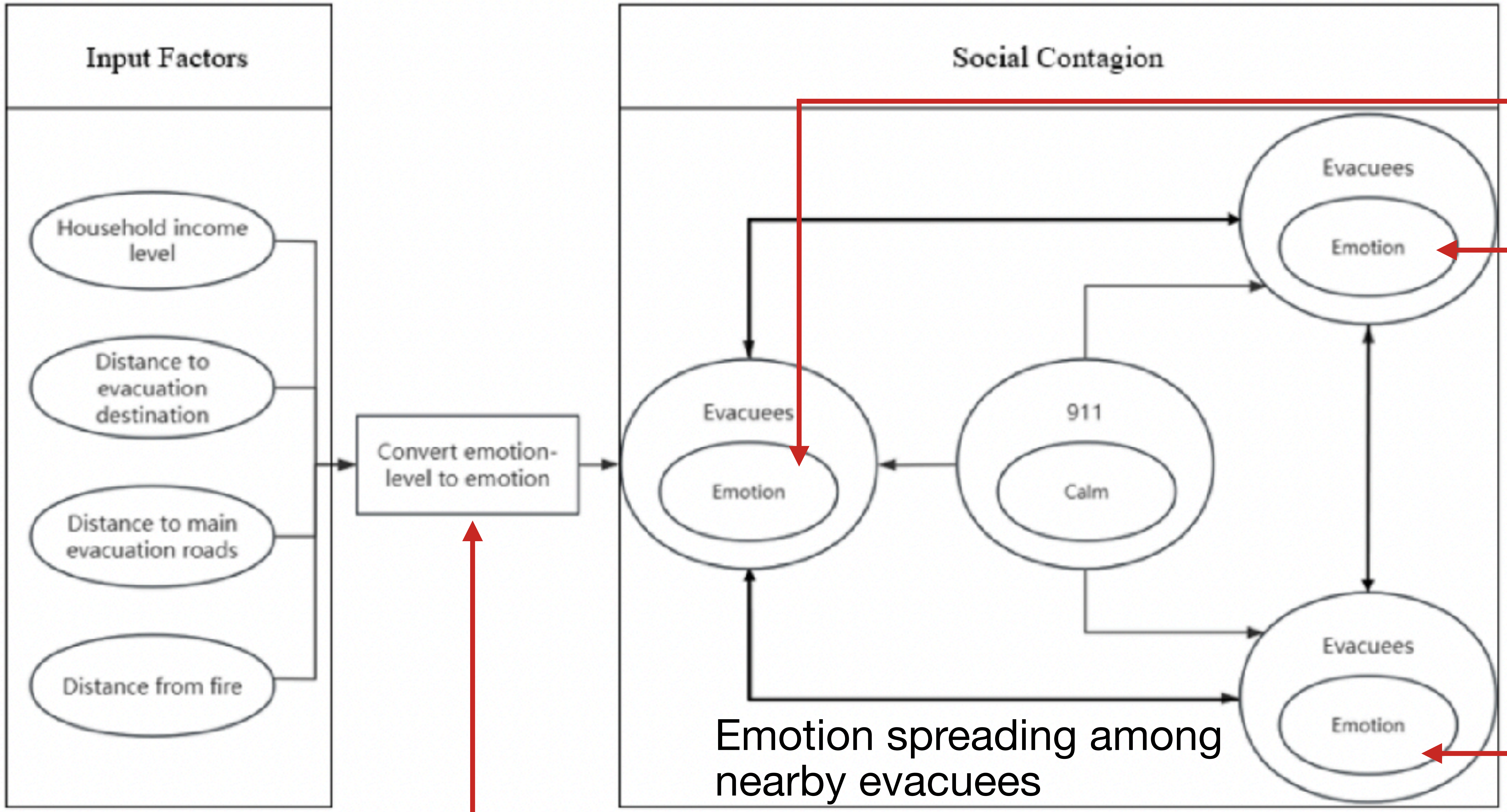


$$p_i = tanh\ (\beta_1 income_i + \beta_2(1 - \frac{d_{exit}}{200}) + \beta_3(1 - \frac{d_{road}}{200}) + \beta_4(1 - \frac{d_{fire}}{200})\ +\ \beta_5 SI_i$$

Emotional Updates (Embedded FCM)

Agent-level Embedded FCM loop with Social Contagion



Integrated social impact & Emotional coupling matrix

$$SIi = \frac{\sum k \in Niwd(k) C_{b_k b_i} p_k}{\sum k \in Niwd(k) C_{b_k b_i}}$$

$$C = \begin{matrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.1 & 0.5 \\ 0.2 & 0.3 & 0.1 \end{matrix}$$

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Emotional Updates (Embedded FCM)

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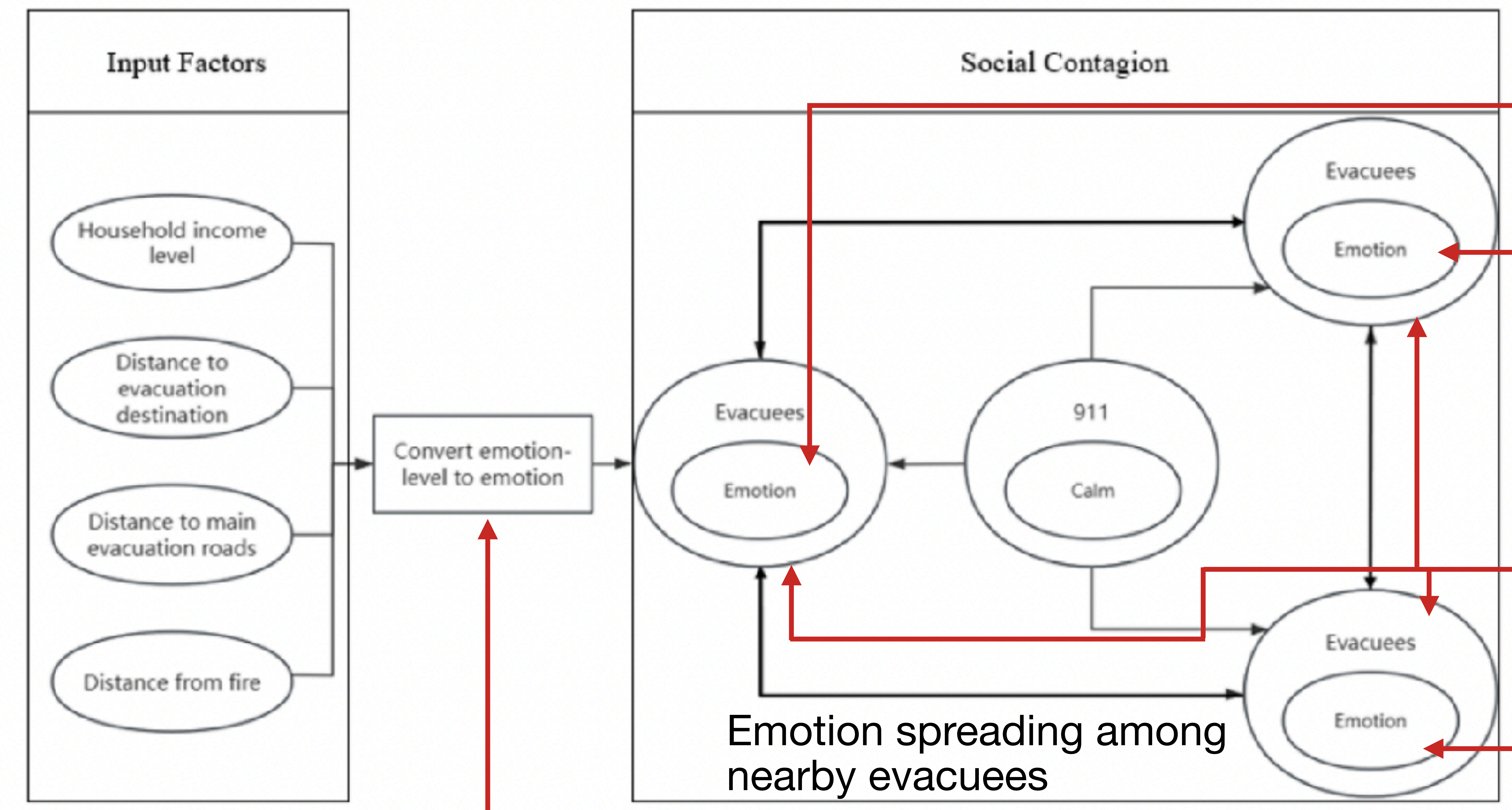

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$$C = \begin{matrix} 0.1 & 0.2 & 0.3 \\ 0.4 & 0.1 & 0.5 \\ 0.2 & 0.3 & 0.1 \end{matrix}$$

$$Ni = \{k, \mid dist(i, k) \leq Rsk \neq i\}.$$

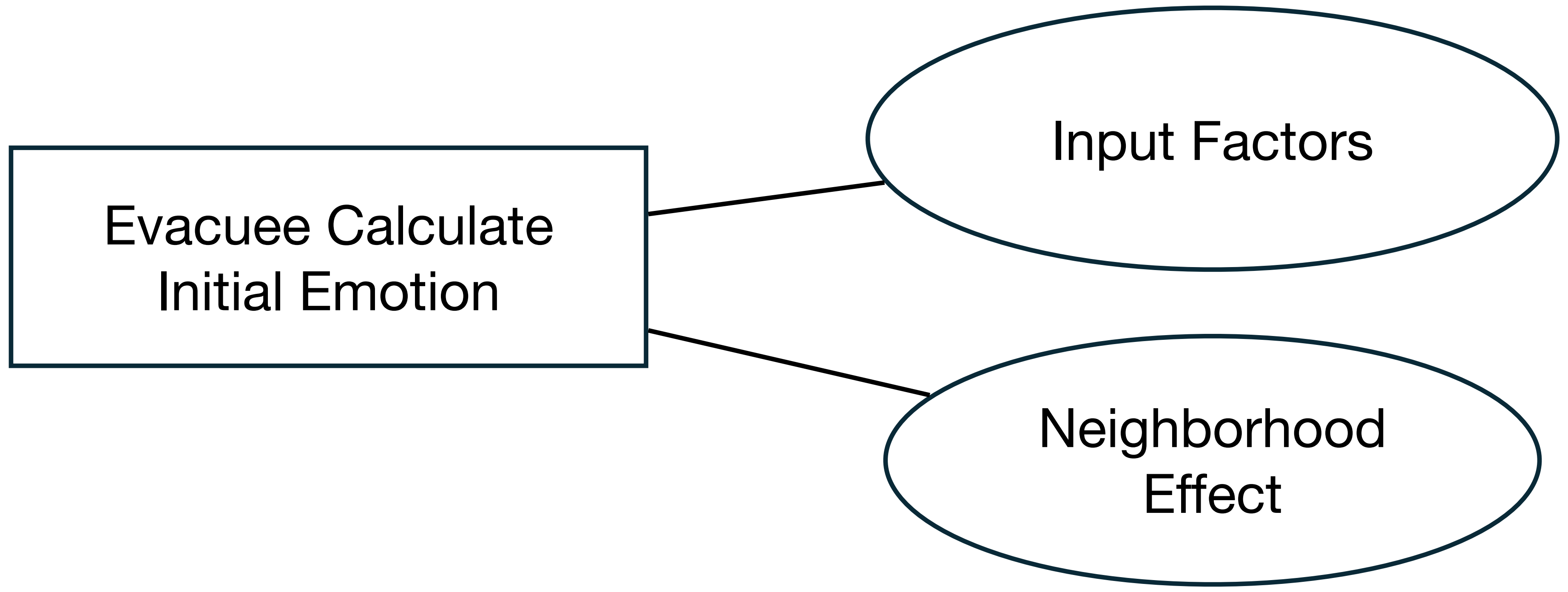
$$w_d(k) = \frac{1}{1+dist\,(i,k)1}$$

Social Contagion & Distance decay weights:

$$p_i = tanh\,(\beta_1 income_i + \beta_2(1 - \frac{d_{exit}}{200}) + \beta_3(1 - \frac{d_{road}}{200}) + \beta_4(1 - \frac{d_{fire}}{200})\; + \; \beta_5 SI_i$$

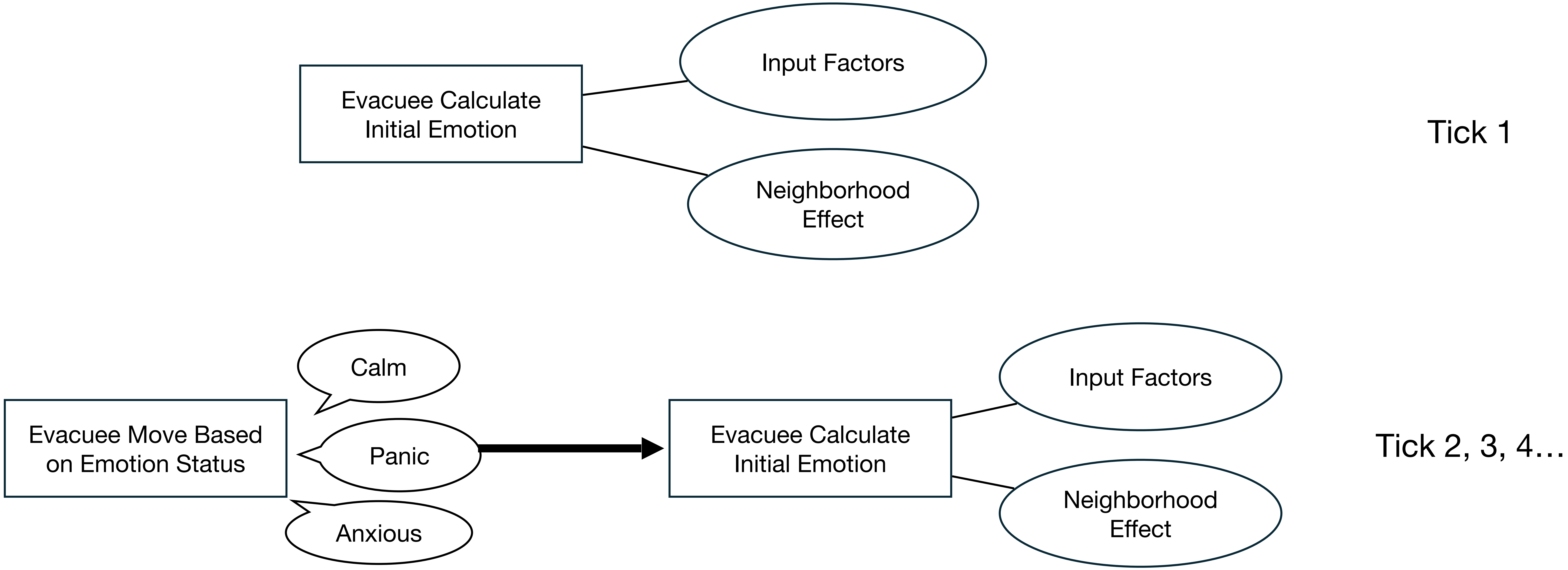
Emotional Updates (Embedded FCM)

Evacuees' Workflow

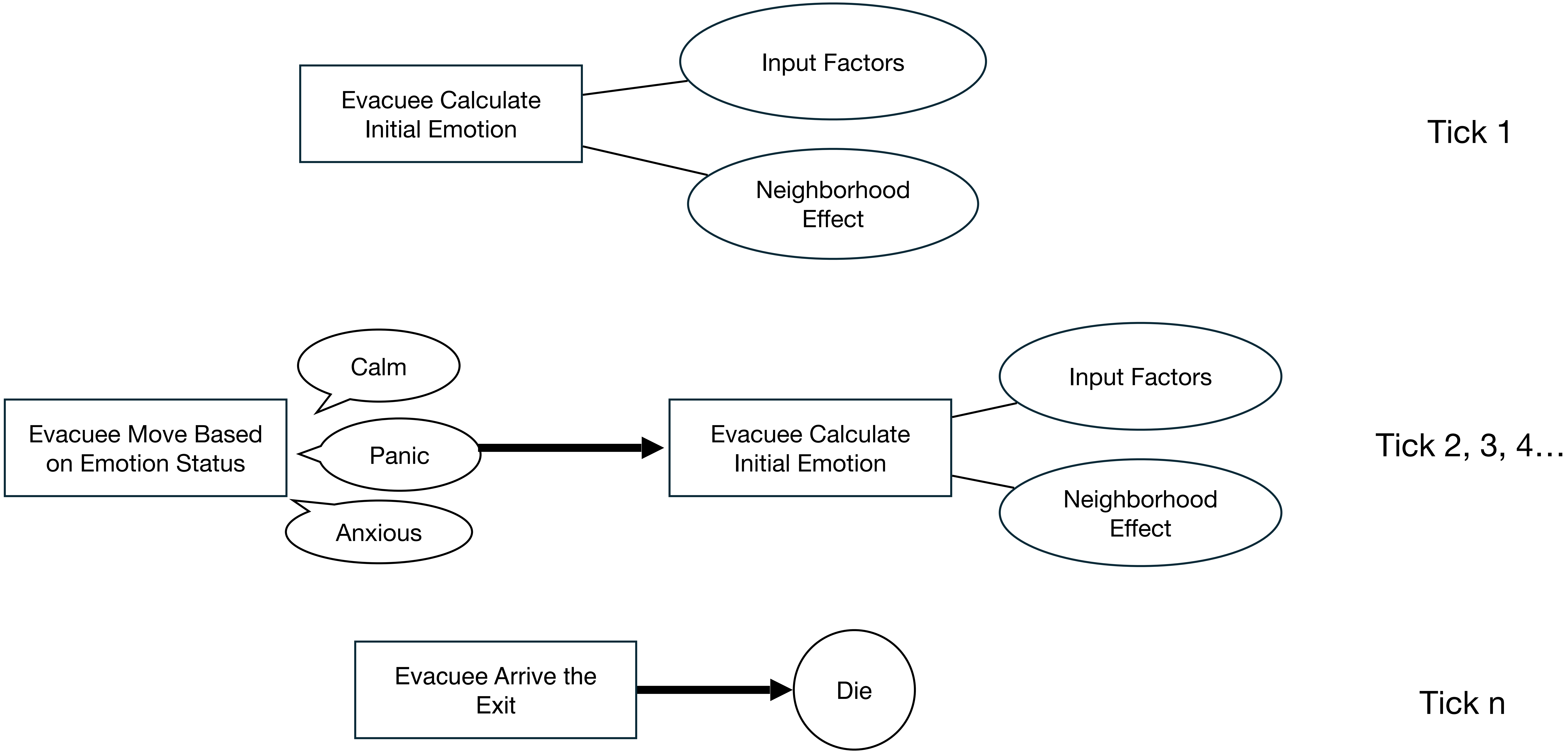


Tick 1

Evacuees' Workflow



Evacuees' Workflow

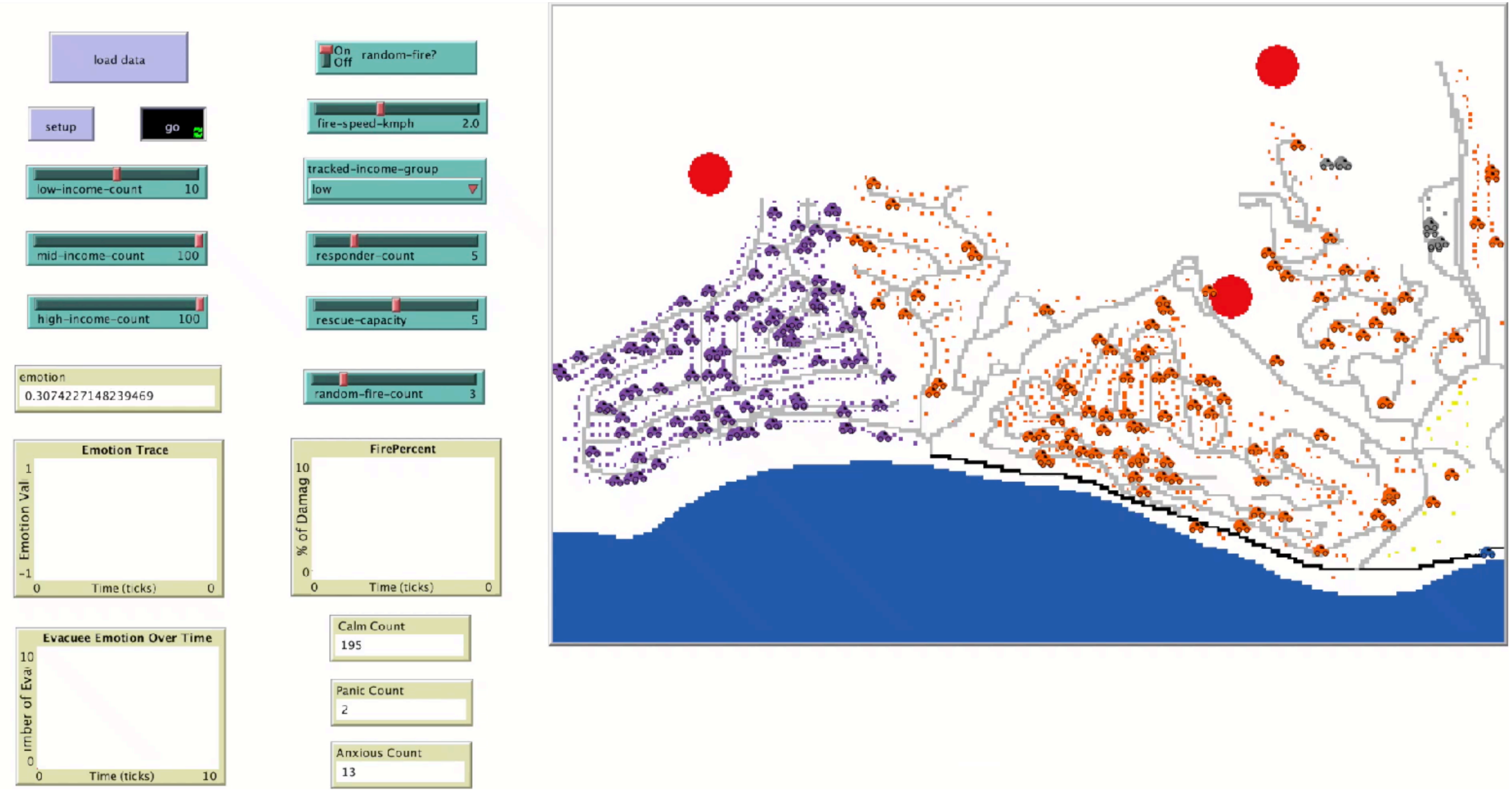


Model Parameters

Parameter	Variable Choices	Default Value	Role
fire-speed	1–8 km h^{-1}	2km h^{-1}	Controls radial growth of the fire fronts each tick
random-fire?	{true, false}	true	Toggles random ignition versus fixed ignition cells
random-fire-count	2-7 points	3 points	Number of ignition spots when random-fire? = true
low-income-count	0-20 agents	10	Population of the low-income group
mid-income-count	0-200 agents	100	Population of the mid-income group
high-income-count	0-200 agents	100	Population of the mid-income group
responder-count	0-20 vehicles	5	Number of emergency response vehicles deployed
rescue-capacity	1-10 persons	5 persons	Maximum evacuees a responder can carry
tracked-income-group	{low, mid, high}	low	Toggle income groups that need to capture emotional levels

Example Model Run

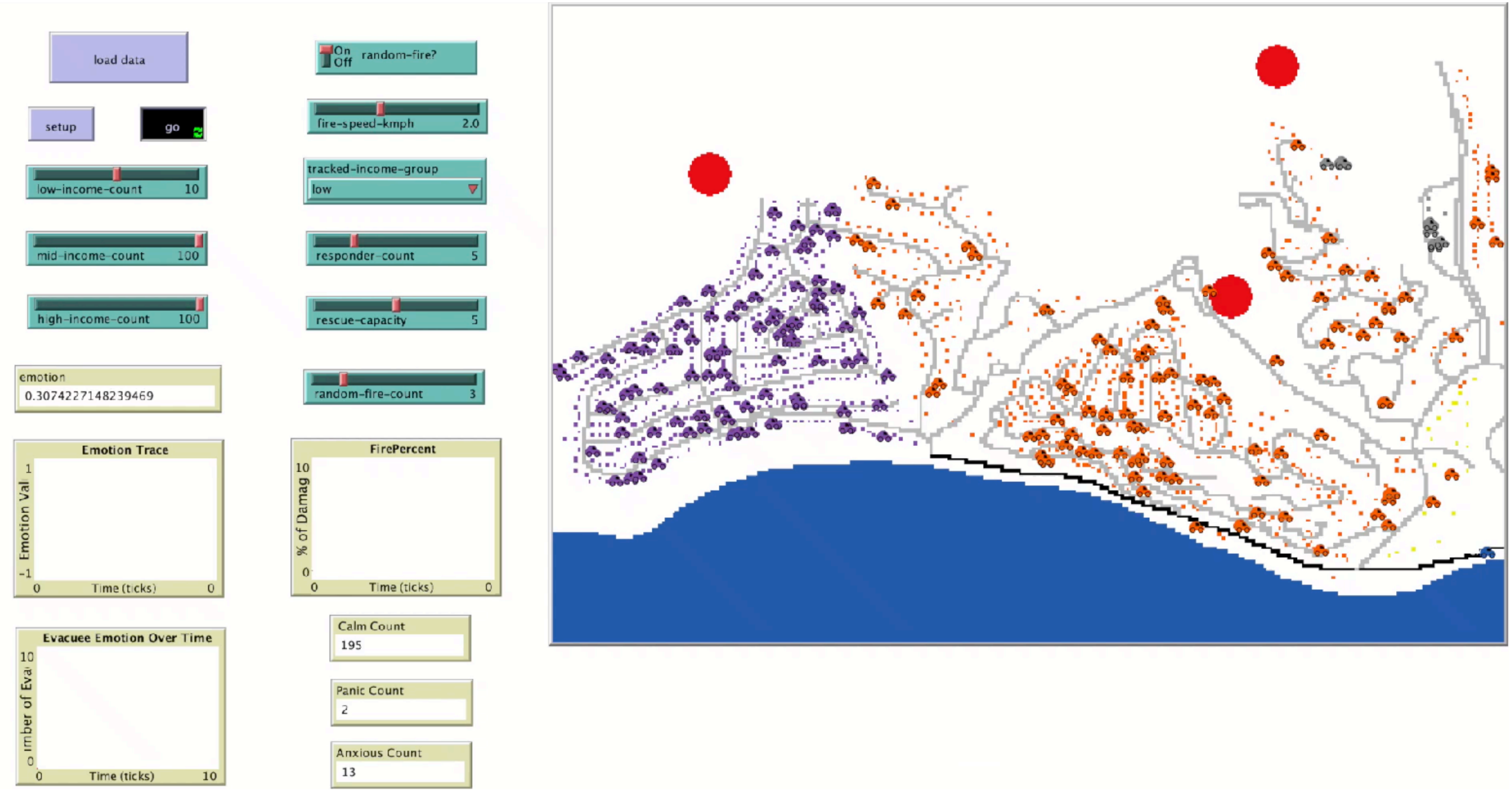
High Income
Mid Income
Low Income
Responders



Calm
Anxious
Panic

Example Model Run

High Income
Mid Income
Low Income
Responders



Calm
Anxious
Panic

Model Verification

- Conducted **code review** and **unit testing** on the model. For example:
  - Reviewed the NetLogo code line by line to verify variable naming and loop boundary settings.
  - Unit tests were written for critical processes (A* pathfinding, traffic capacity check, FCM mood update) to ensure that the output matched the manual calculation results.
- Additionally, **extreme value** and **outlier tests** were performed.
- For example:
  - We set the number of evacuated vehicles, fire spread speed, and FCM edge weights to 0 and their maximum theoretical values,
  - Used NetLogo's BehaviorSpace to batch-ran different parameter combinations
    - (e.g., the number of people in each income class, wildfire spread speed, and random wildfire count)
  - Recorded the abnormal termination rate (currently 0%).

Model Validation

- Here, we choose the Axtell and Epstein (1994) model validation system.
  - Level 0 validation refers to models that are merely graphical "*caricatures*" of reality, used to qualitatively demonstrate agent behavior
  - Level 3 models are *quantitatively* consistent with real data at the *micro level behavior*.
- Our aim is to achieve **level 1 validation** where the model is qualitatively consistent with reality at the macro level.

Axtell, R.L., Epstein, J.L.: Agent-based modelling: Understanding our creations. *The Bulletin of the Santa Fe Institute* pp. Winter, 28–32 (1994)

Model Validation

Traffic Congestion

- **Long-term monitoring data** from the California Department of Transportation (2025) shows that the intersections of Highway 1 and other secondary roads are most prone to ***sudden drops in vehicle speed during emergency evacuations***.

- In our simulations we observed that similar congestion hotspots frequently occur at similar nodes.
  - This indicates that the **A* path planning**, **road capacity settings**, and **vehicle congestion avoidance strategies** in the model accurately capture key network constraints.

California Department of Transportation: Caltrans Performance Measurement System (PeMS) [Dataset] (2025), https://pems.dot.ca.gov/

Model Validation

Socioeconomic Differences Influence Emotions

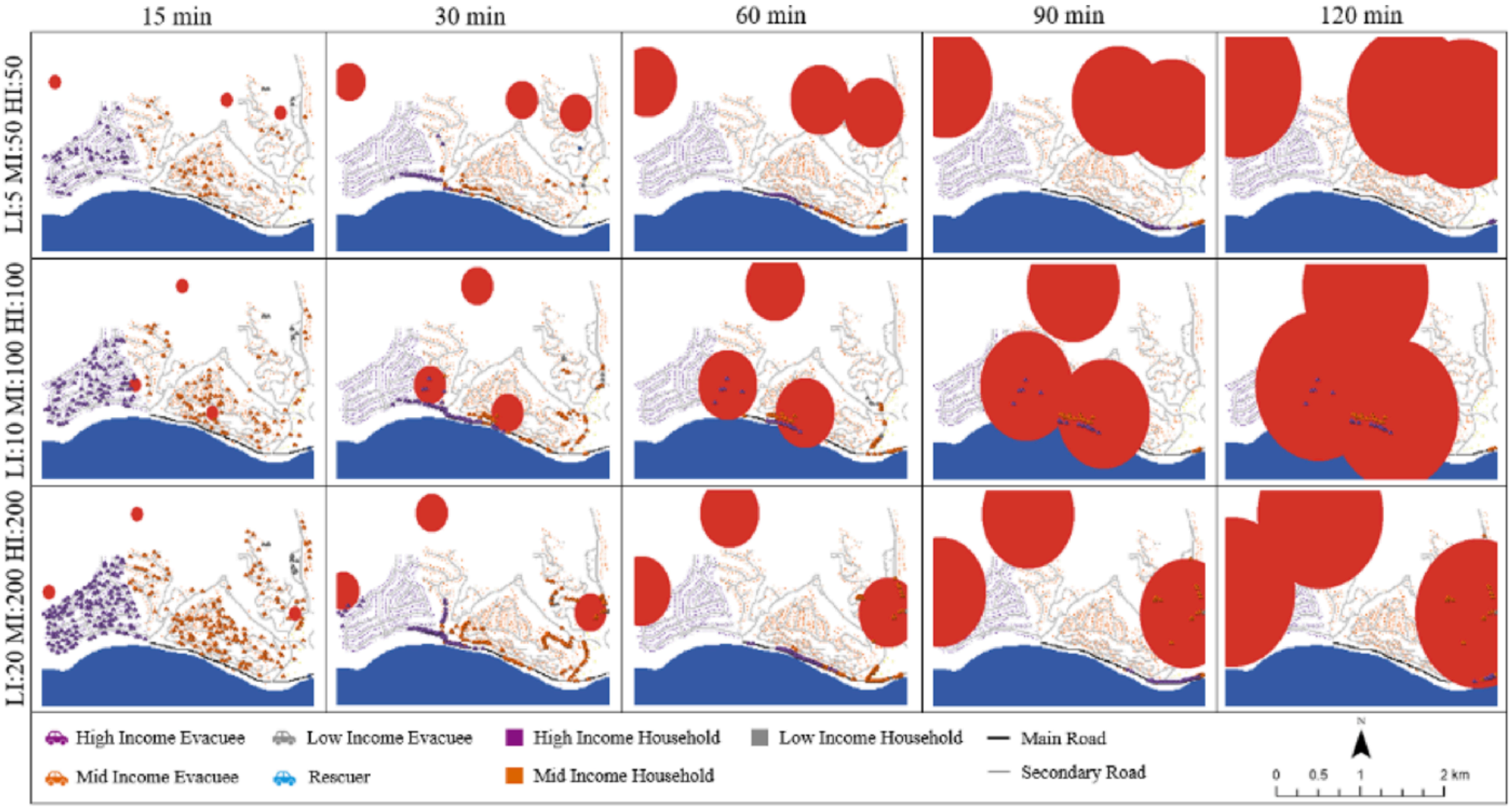
- Recent investigations into multiple wildfires in California indicate that **low-income or vulnerable communities** often **initiate evacuations earlier** to mitigate uncertainty caused by resource shortages.

- In our model, we categorized evacuees into three income tiers and **found that the average emotional level of the lowest-income group was higher than that of the other two groups**.
  - This result validates our assumption in the FCM that income level influences emotional level.

- Based on these comparisons we can conclude that the model has passed the Level 1 validity test.

California Department of Transportation: Traffic modeling of potential emergency wildfire evacuation routes (2021), https://dot.ca.gov/-/media/dot-media/programs/research-innovation-system-information/documents/preliminary-investigations/pi-0278-a11y.pdf

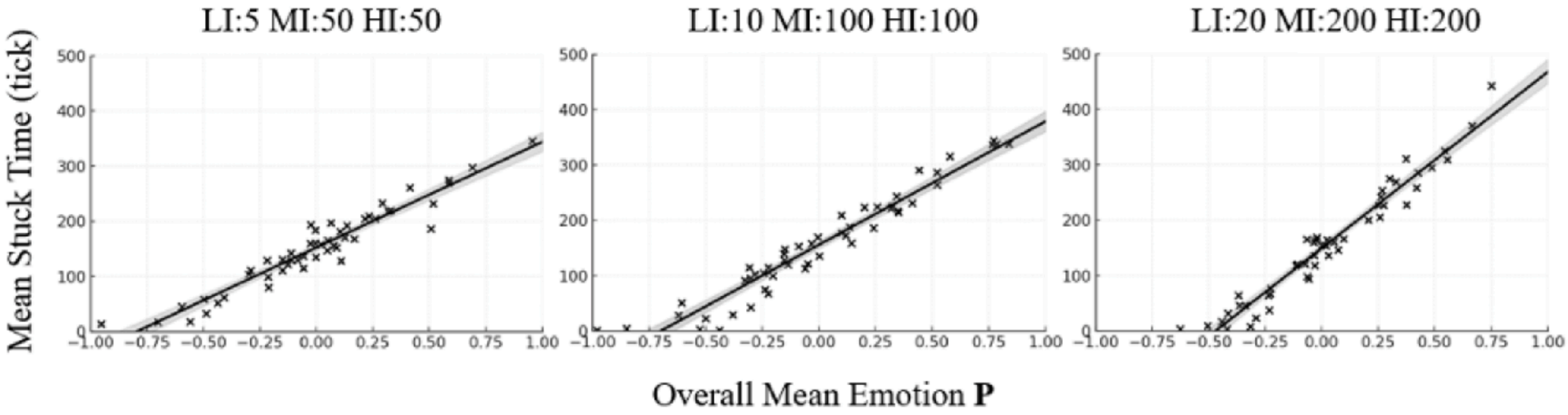
Results: Increasing Numbers of Agents across Different Income Levels



Representative model time series diagrams, with the numbers on the left indicating the number of evacuees in each income bracket corresponding to each set of simulations. Low Income (LI), Middle Income (MI), High Income (HI).

Results

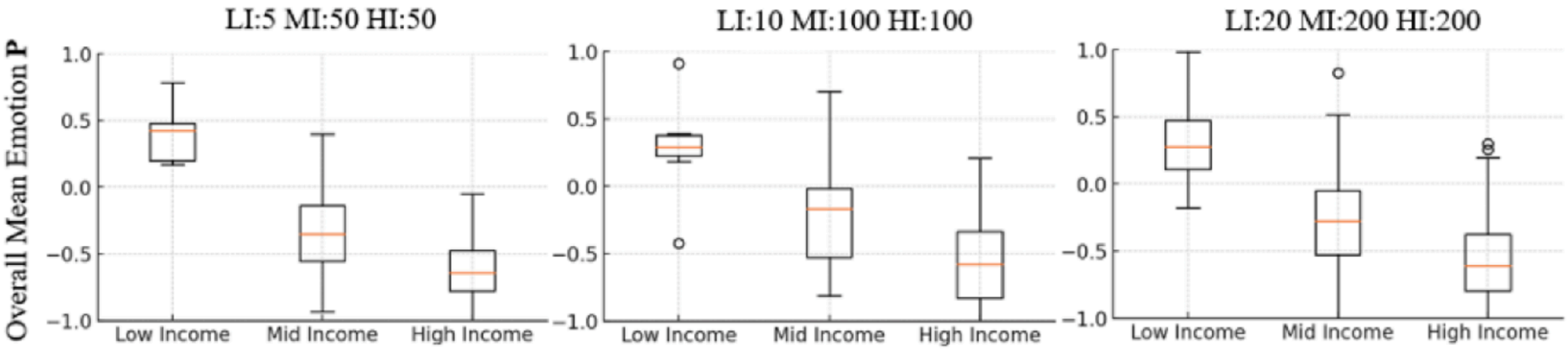
Emotional Levels and Behavioral Performance



The relationship between overall mean emotion **P** and mean stuck time to standstill. Shaded for 95% confidence bands. Increasing number of people in each income bracket in the three groups from left to right. Low Income (LI), Middle Income (MI), High Income (HI).

Results

Linkage of Income, Emotions and Behavior



Box plots of average emotions for three groups of experiments (50 repetitions each). From left to right, the number of people in each income group increases progressively. Low income (LI), middle income (MI), and high income (HI).

Results

Linkage of Income, Emotions and Behavior

- To explore the pathway of "income → emotion → behavior" we applied the Baron–Kenny method for mediation analysis, which involves three regression steps.

  1. The regression (income → behavior) showed that for each decrease in income level (high → medium → low), the stuck time increased by ~43 ticks, showing a positive trend.

  2. The regression (income → emotion) showed that income also had a positive effect on emotion.

  3. When emotion level is included in the regression along with income, the **coefficient for emotion is significant**, while the coefficient for income drops sharply and loses significance.

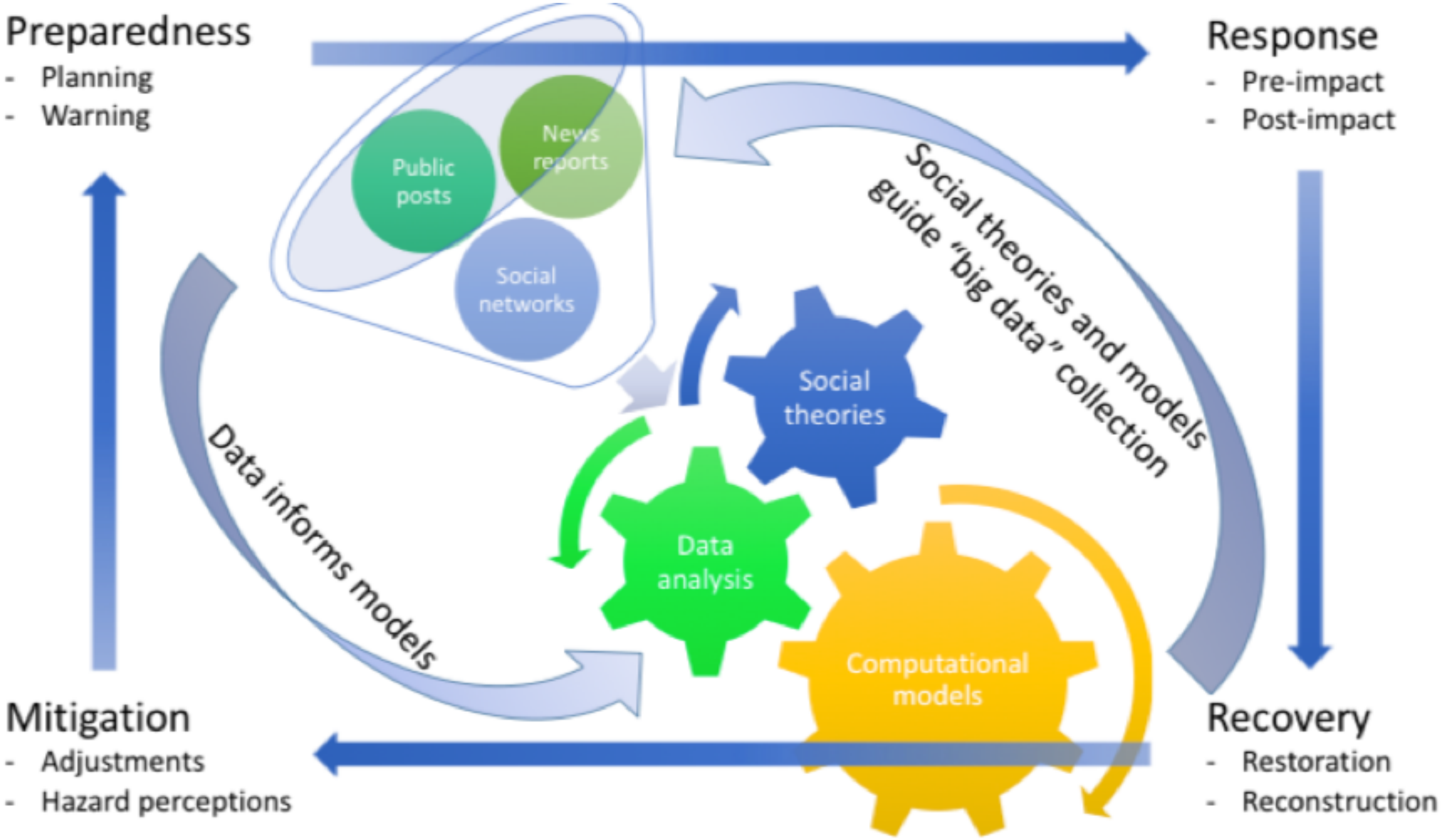
- This result suggests that income's influence on behavior is almost entirely mediated by emotion.

Summary and Outlook

- This study builds upon existing literature on fire evacuation by embedding FCMs into an ABM, with a focus on revealing the previously unquantified causal chain linking “**income→emotion→behavior**”.
- Experimental results indicate that **low-income individuals exhibit higher emotional levels than high-income individuals** under identical external conditions.
- This finding aligns with post-disaster field surveys that identified a chain reaction among low-income households characterized by “**low preparedness→high fear→disorganized action**”
- Further work could explore access to resources, communication channels to mitigate panic, realistic fire model etc…

Looking Ahead

- Model only focused on **immediate and urgent aspects of the incident** (i.e. response).
- However incident management is complex:
  - What about the long term **recovery** and **mitigation**?



Burger, Oz, Kennedy & Crooks (2019), Computational Social Science of Disasters: Opportunities and Challenges, *Future Internet*, 11(5): 103;

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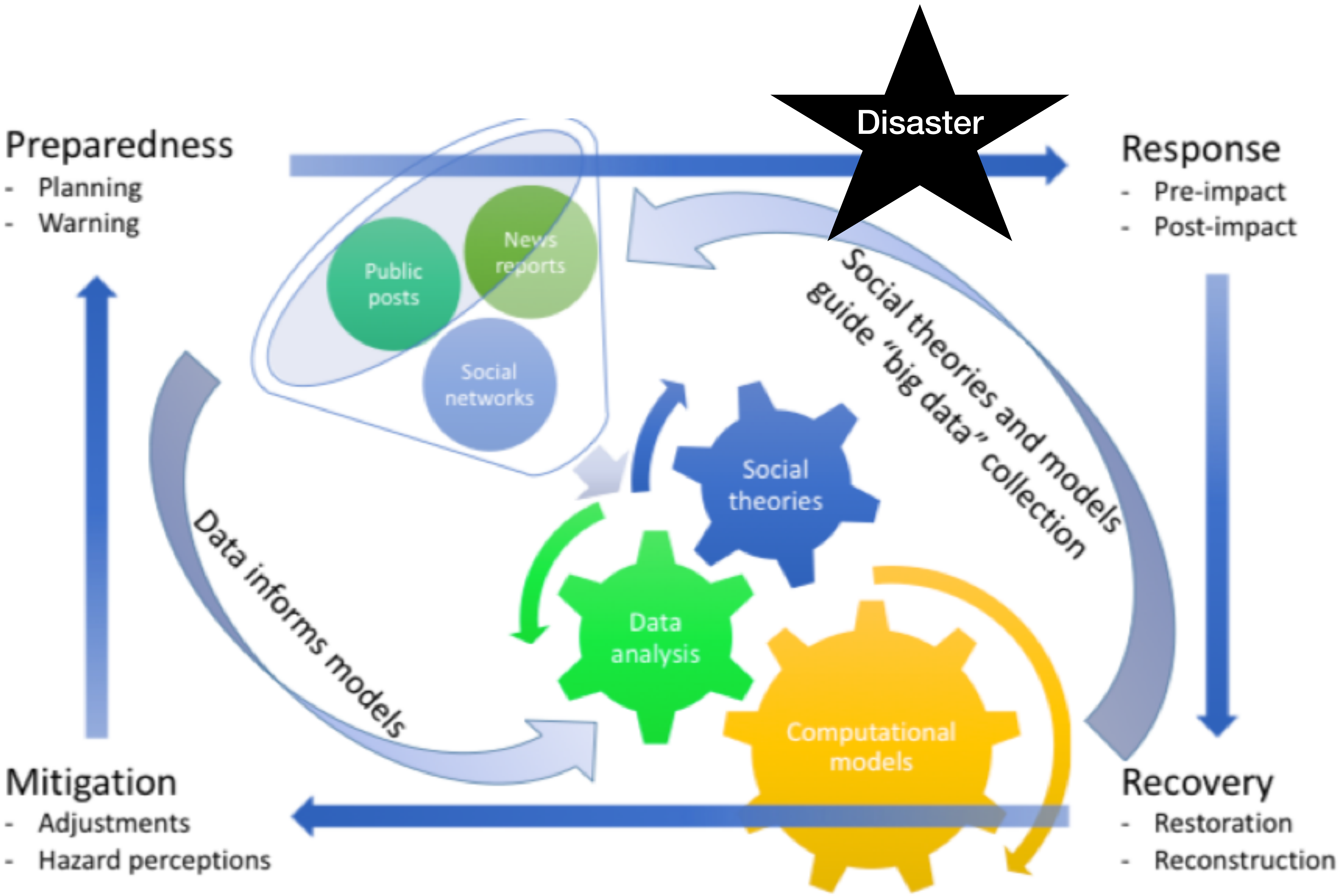
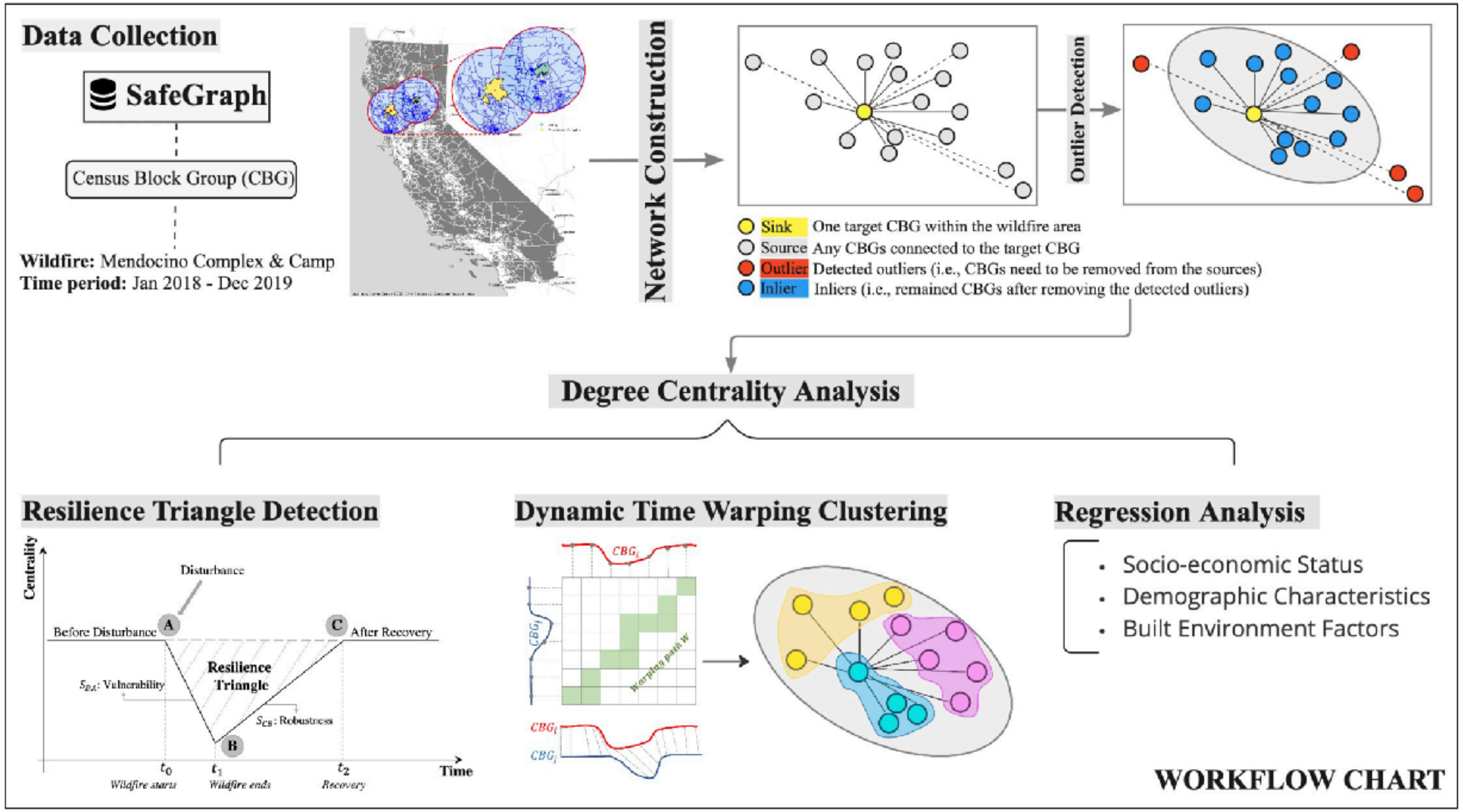


Burger, Oz, Kennedy & Crooks (2019), Computational Social Science of Disasters: Opportunities and Challenges, *Future Internet*, 11(5): 103;

Community Resilience to Wildfires

A network analysis approach by utilizing human mobility data



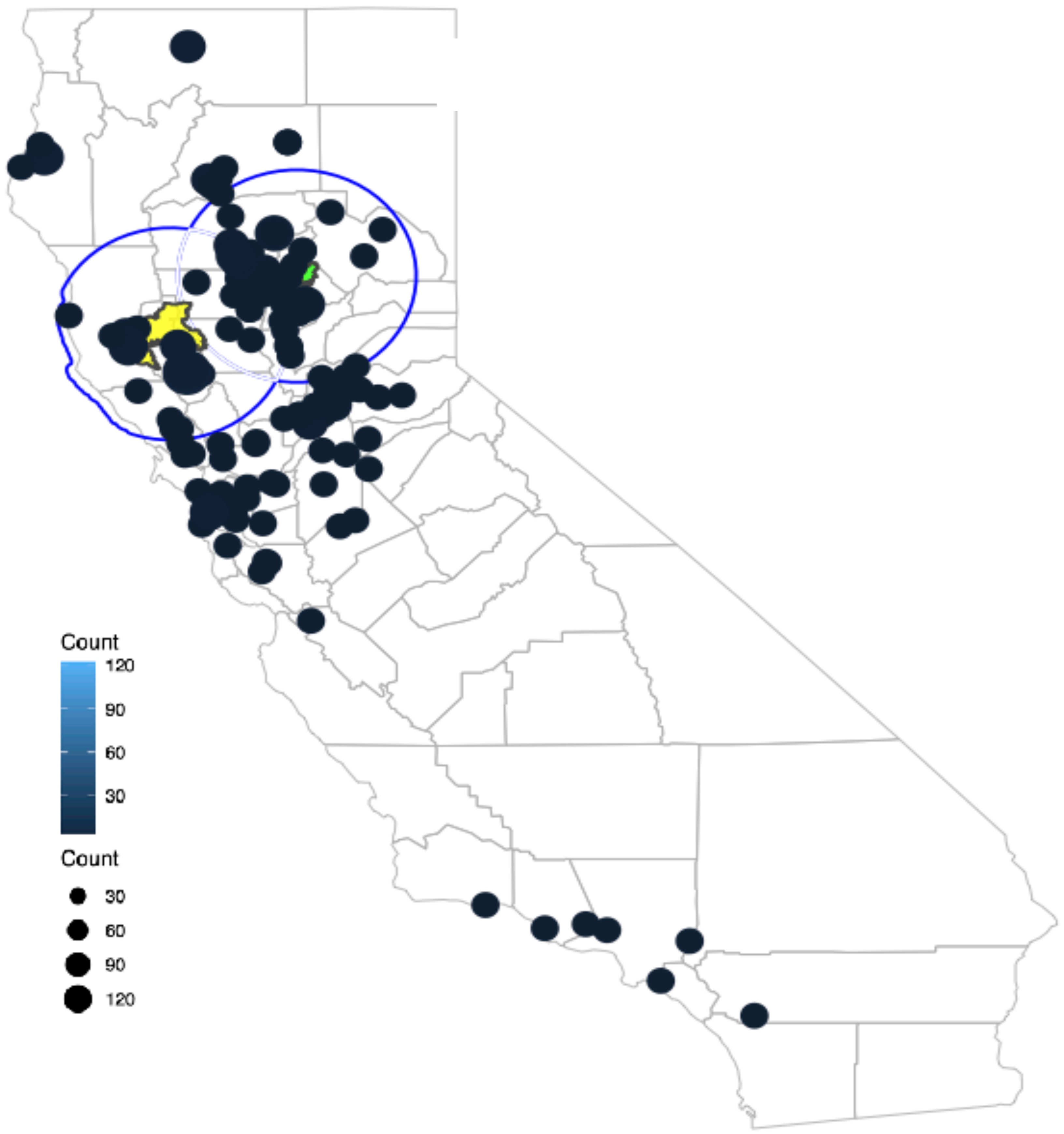
- Which community is more resilience compared to others and why?
- Did a community bounce back to its original status after a certain time or form a new normalcy?
- What are the similarities and differences among communities?

Chen, Q., Wang, B. and Crooks, A.T. (2024), Community Resilience to Wildfires: A Network Analysis Approach by Utilizing Human Mobility Data, *Computers, Environment and Urban Systems*, 110: 102110.

Resilience Detection

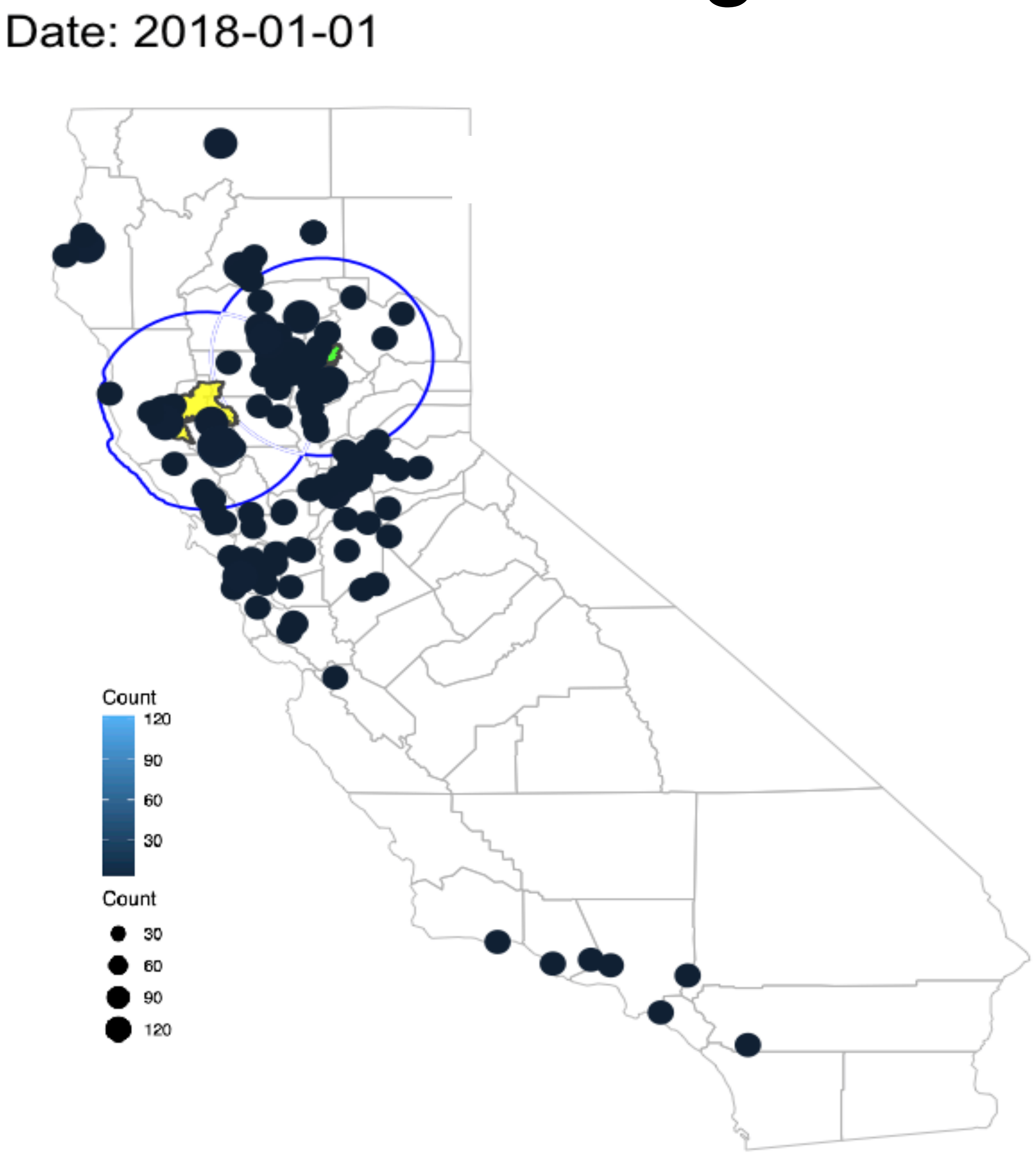
Network & Degree Centrality

Date: 2018-01-01



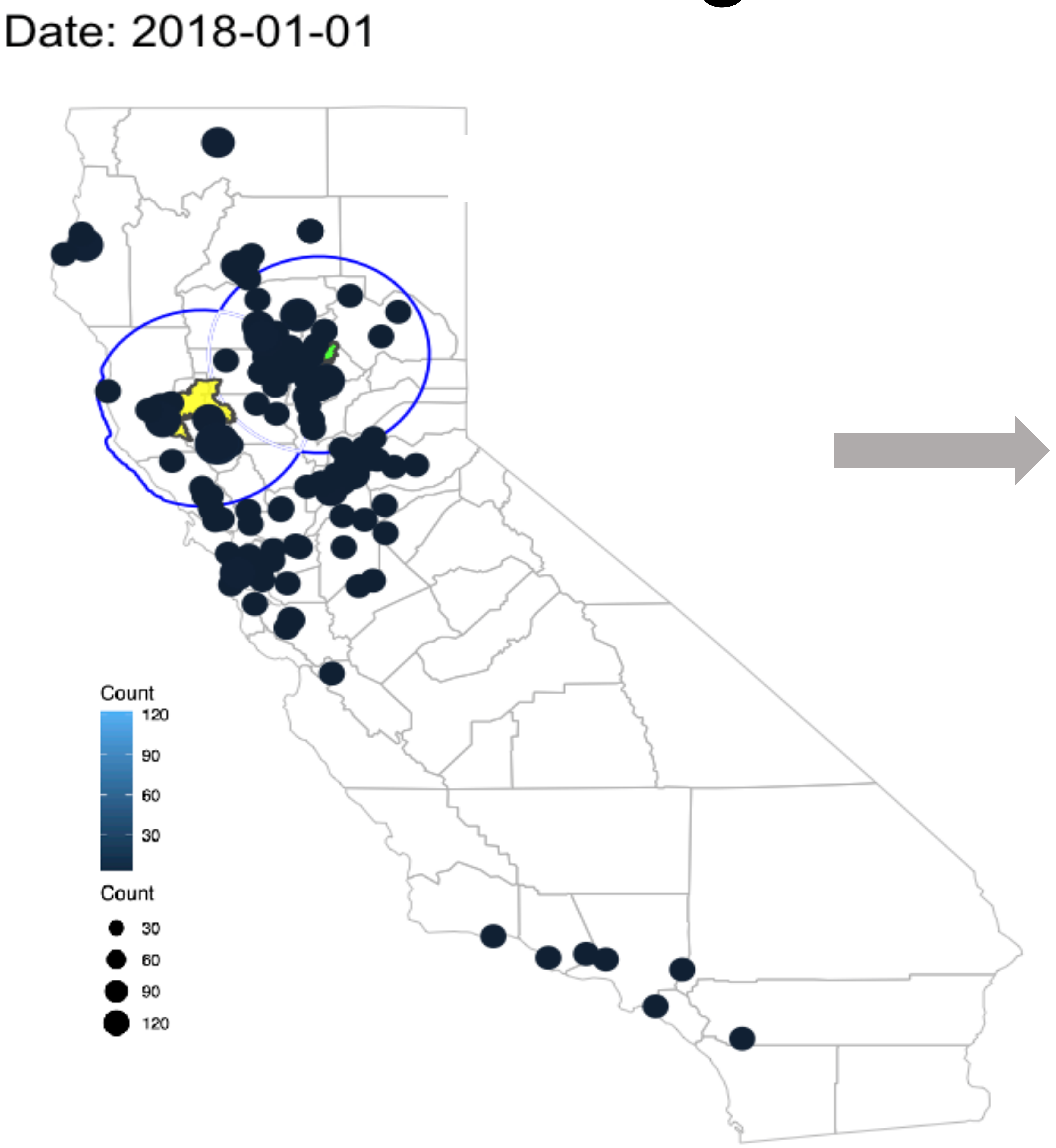
Resilience Detection

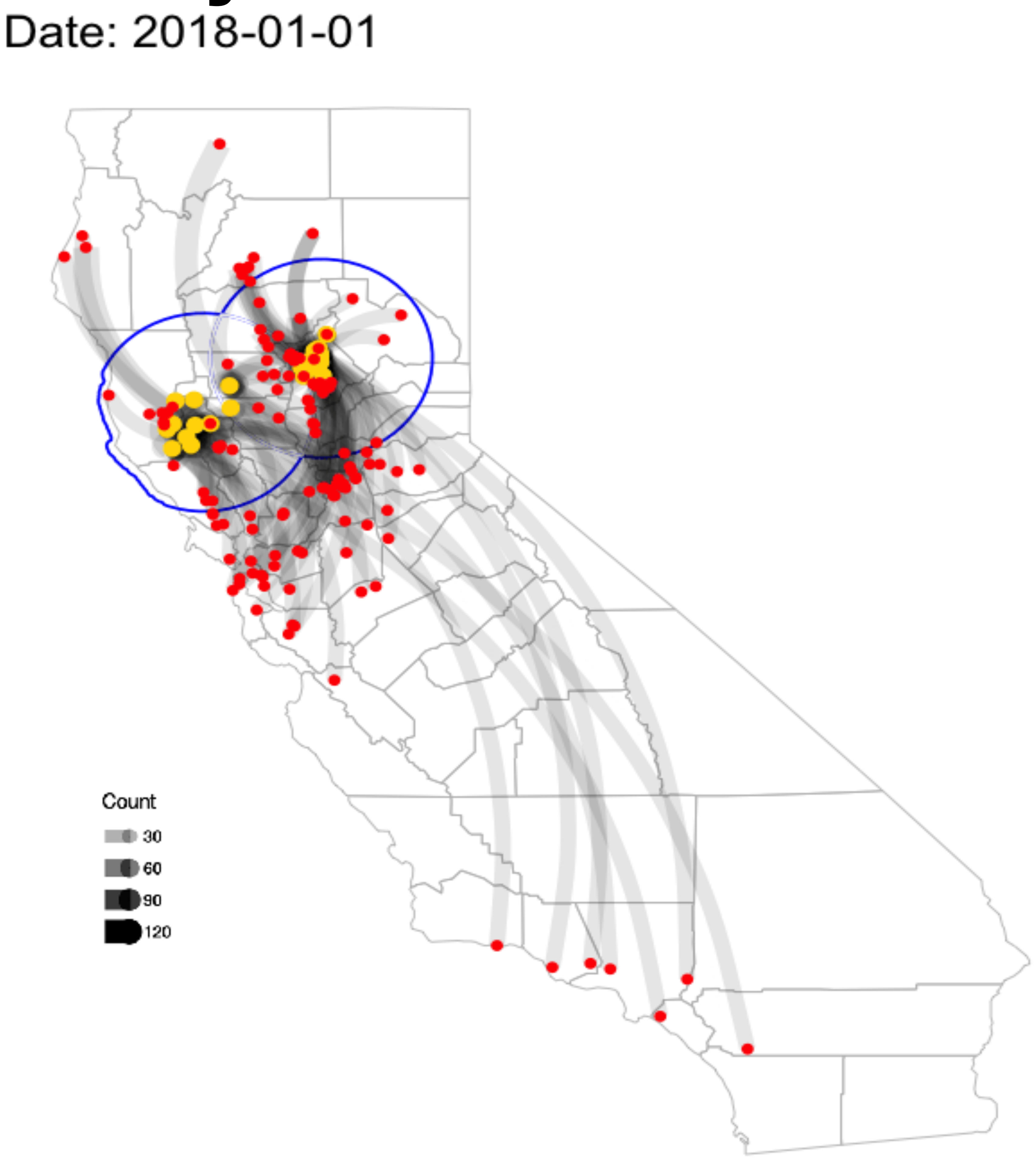
Network & Degree Centrality



Resilience Detection

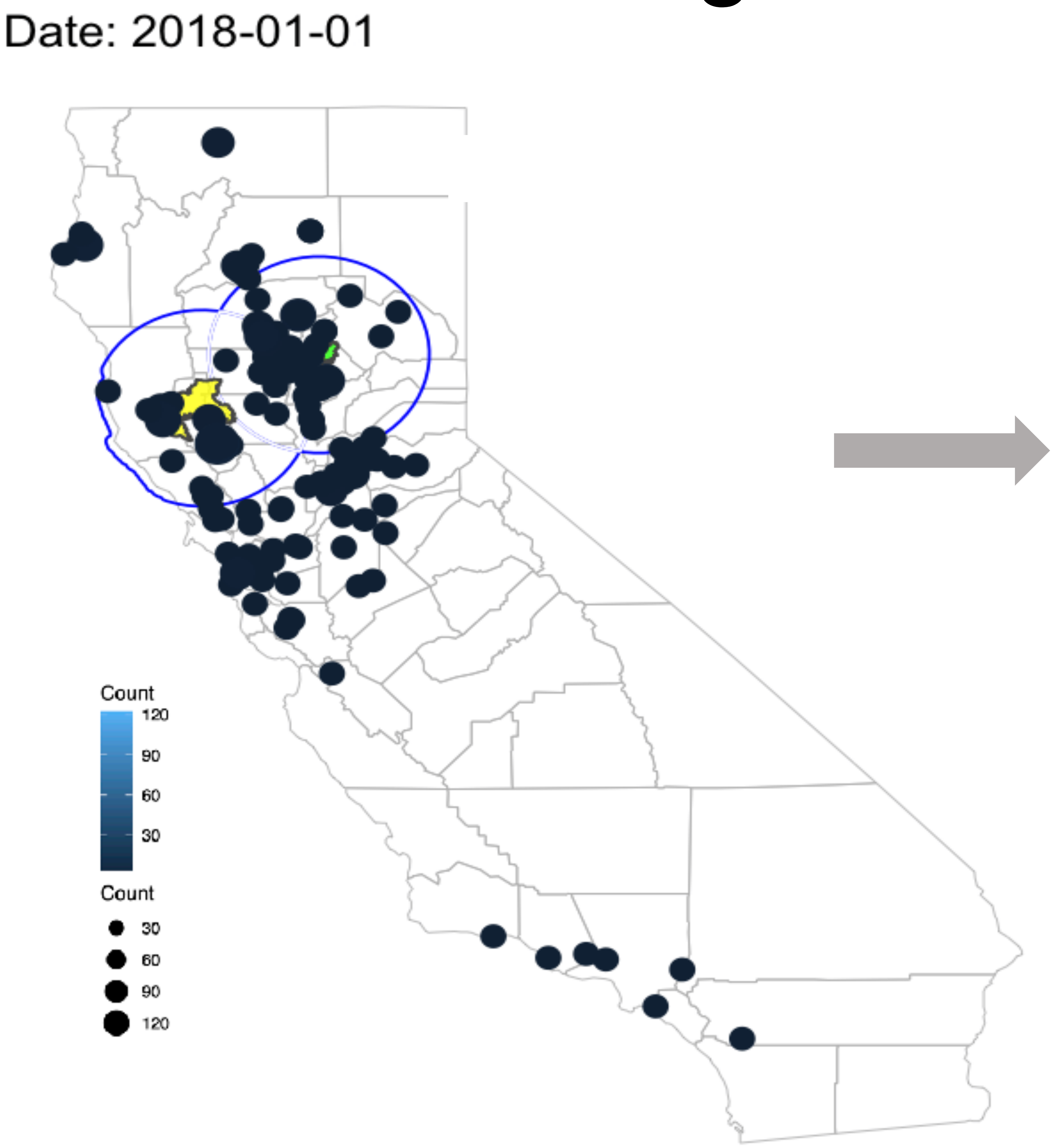
Network & Degree Centrality

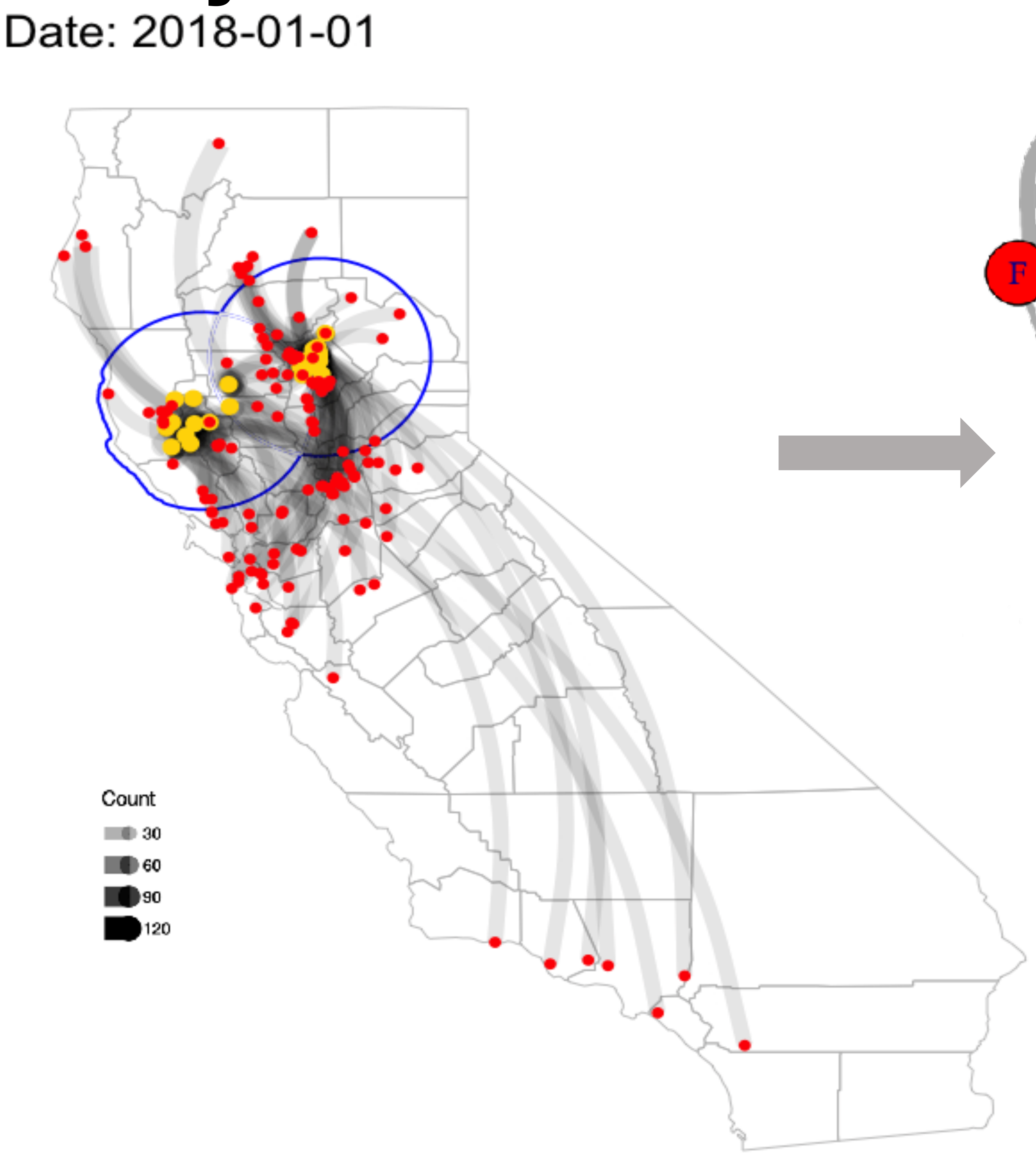


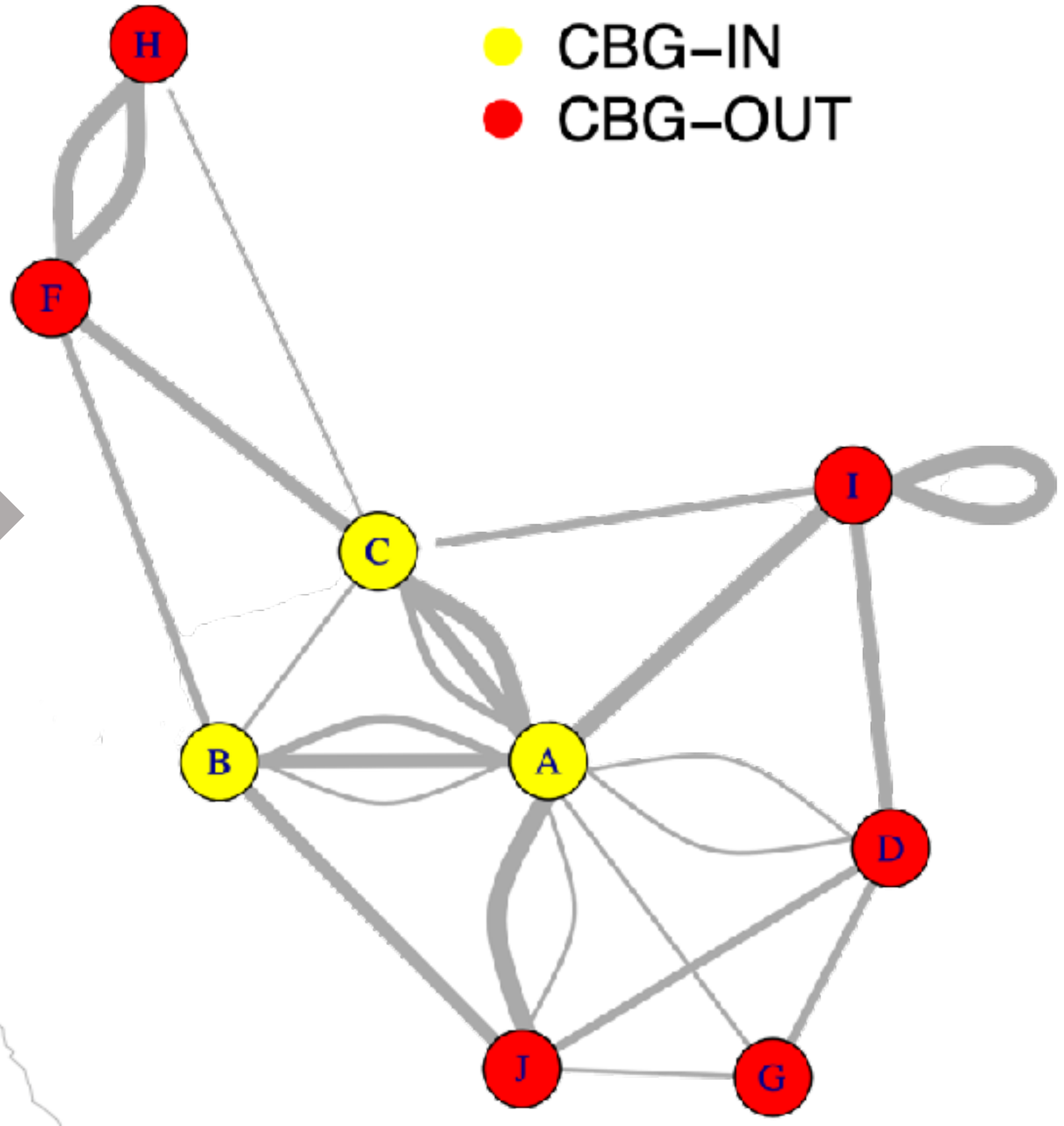


Resilience Detection

Network & Degree Centrality



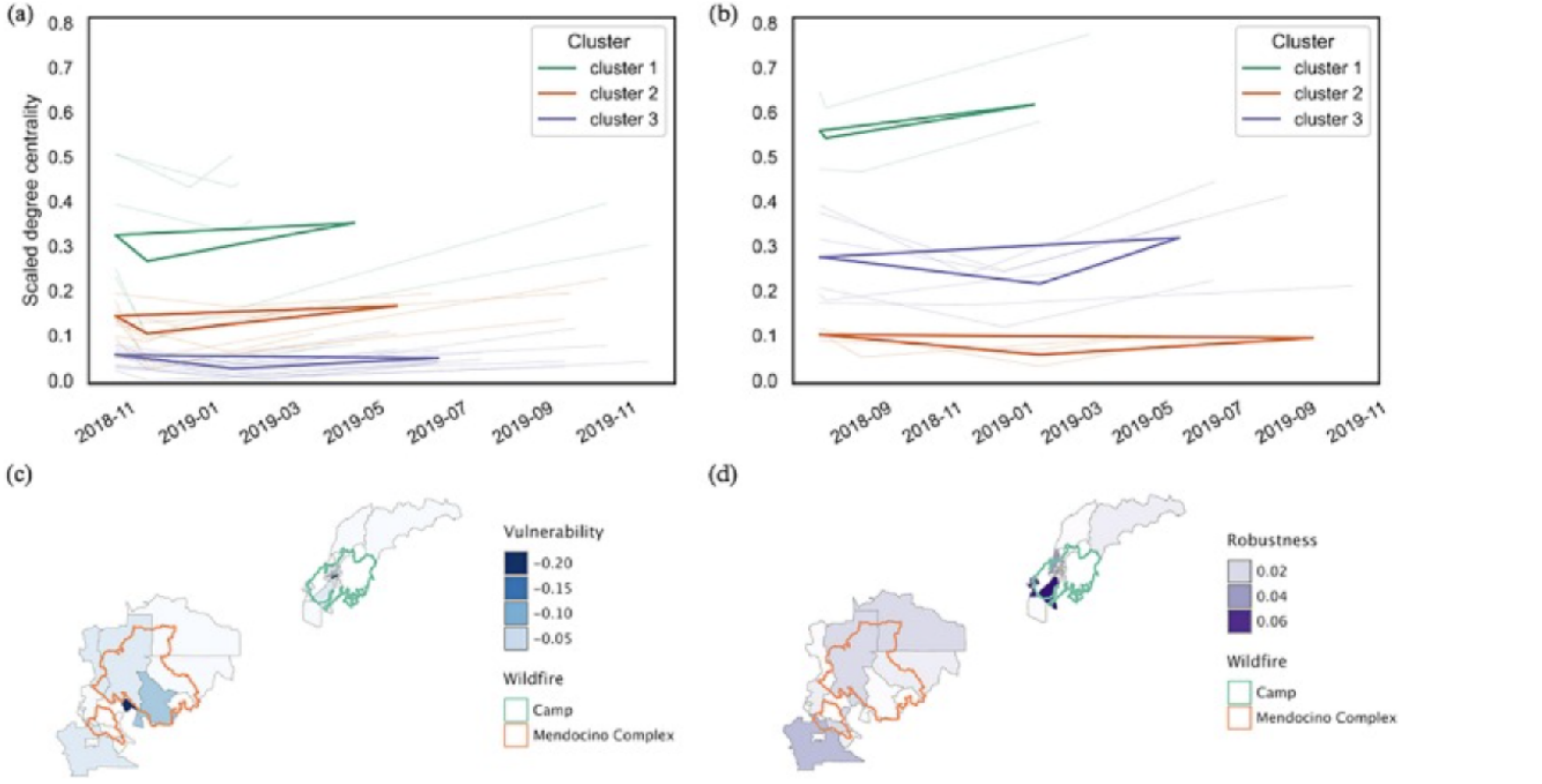




Findings

Camp wildfire

Mendocino wildfire



The results of resilience triangles of clustered CBGs and resilience features. The determined resilience triangles of clustered CBGs for Camp (a) and Mendocino Complex wildfires (b), (c) Vulnerability of CBGs within the two wildfire areas; (d) Robustness of CBGs within the two wildfires.

Urban Analytics and City Science

EPB: Urban Analytics and City Science
2025, Vol. 52(3) 523–526

DOI: 10.1177/23998083251323145
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Cities and disasters: What can urban analytics do?

Images of the devastating wildfires impacting parts of Los Angeles County in early January of this year were seen all over the world. While reading the New York Times the other day, I stumbled across an article from February 1st (Jiménez, 2025) that reported that the Eaton and Palisades fires were fully contained, or, in other words, under control as of the 31st of January. These devastating wildfires started on the 7th of January and over the span of several weeks killed 29 people and displaced thousands of others. The Palisades and Eaton fires destroyed over 16,200 structures (not to mention damaging many others) and burnt over 37,469 acres (roughly 150 km^2). During these wildfires, nearly 192,000 residents faced mandatory evacuations and another 140,000 were subject to warnings (Rodriguez, 2025). While these fires might not be the most destructive or deadliest (e.g., the Camp wildfire in 2018) or the largest (e.g., the August Complex wildfire in 2020) in Californian history (CAL Fire, 2025), they are some of the largest urban wildfires in recent history (Wildeman and Keller, 2025).

While fires in urban areas are not new—think of the Great Fire of London in 1666 or the Great Chicago Fire of 1871—what is different today is that the fires themselves are not starting within the city by accident, such as a spark from a bakery oven in Pudding Lane that ignited materials in London, but on the outskirts of cities (i.e., the wildland-urban interface (Rojanasakul and Plumer, 2025)). The United States Fire Administration (2025) estimates that 60,000 communities in the United States are at risk from such fires. This is partly because, as the United States and the world's population more generally become more urbanized, cities grow, which causes developments on the outskirts of cities. This trend is not expected to stop in the near future. Furthermore, it is not just fires that impact people; for example, it was estimated that in 2024, 7.7 million people were displaced by earthquakes, floods, and wildfires (Internal Displacement Monitoring Centre, 2024), many of which were in urban areas. The question is thus: how resilient are cities to such events?

Resiliency and cities have been a constant theme in many papers and editorials of this journal. For example, it has been noted how cities are creating initiatives to respond to climate change (e.g., See, 2024) or how the frequency and intensity of disasters is growing and ways to mitigate against them (e.g., Ukkusuri et al., 2021), or how advances in Information and Communication Technologies (ICTs) and data analytics are being used more and more for exploring resilient and sustainable cities (e.g., Sharifi and Yamagata 2022).

In this editorial, I would like to focus on the role of urban analytics and more broadly on the various stages of disaster emergency management (i.e., preparation, response, recovery, and mitigation). Geographical information systems (GISs) have a long history when it comes to disaster management (see Cova, 2005) as it can be used to carry out risk assessments (i.e., how many homes are located in a flood plain), provide situational awareness with respect to the extent of damage, where resources are deployed (e.g., fire crews) along with current weather and traffic conditions, and also aid in post disaster recovery (i.e., which buildings have been destroyed or rebuilt) to name but a few uses. But in keeping with the nature of this journal, that is, urban analytics, which Batty (2019) defined as the "*term analytics implies a set of methods that can be used to explore, understand and predict properties and features of any system, in our case of cities*," the question arises: how can we

Find Out More

University at Buffalo
Institute for Artificial Intelligence and Data Science

BEAMS Initiative

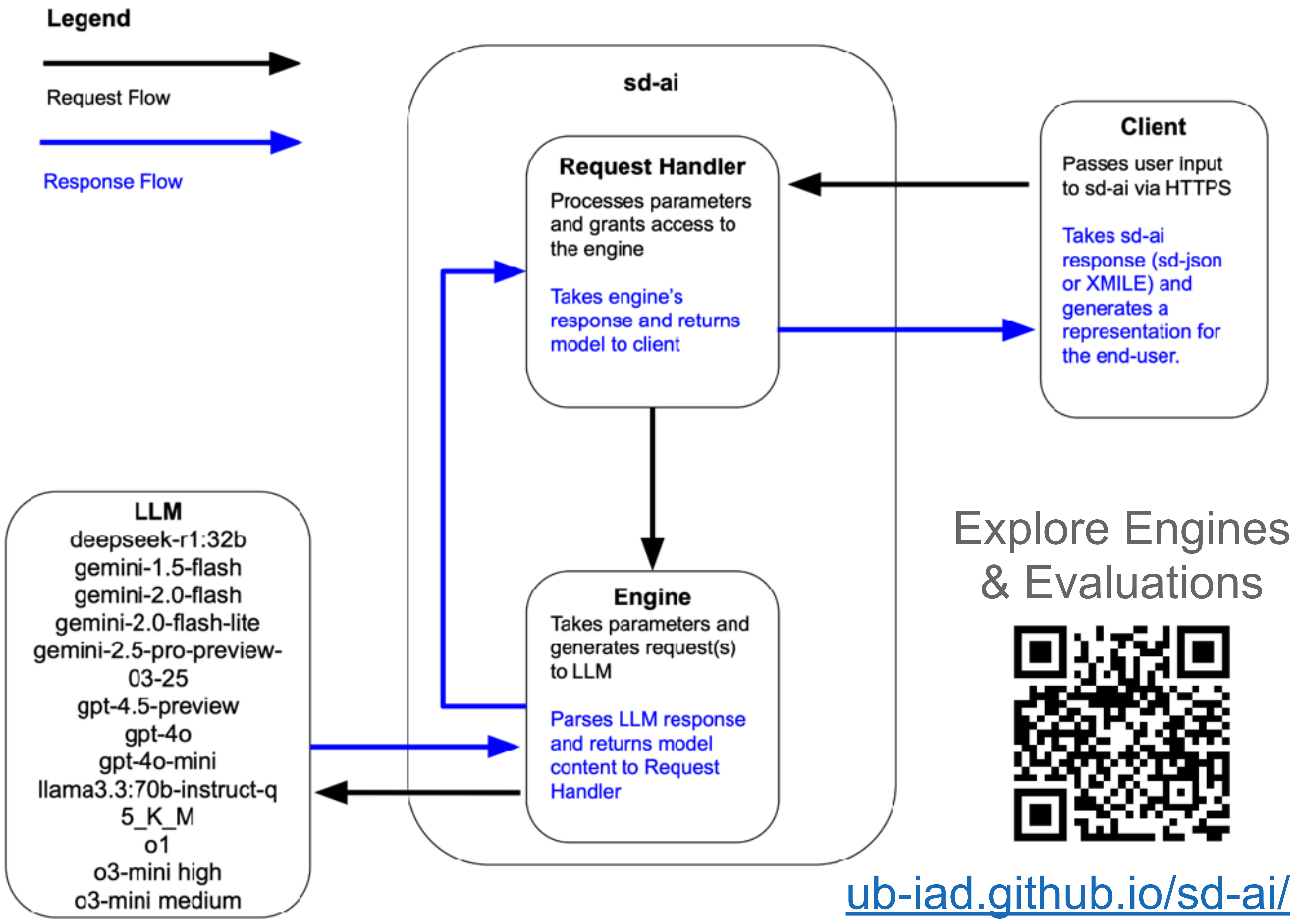
Benchmarking and Evaluating AI for Modeling and Simulation (BEAMS)

BEAMS = Benchmarking and Evaluating AI for Modeling & Simulation

bit.ly/BEAMSinitiative

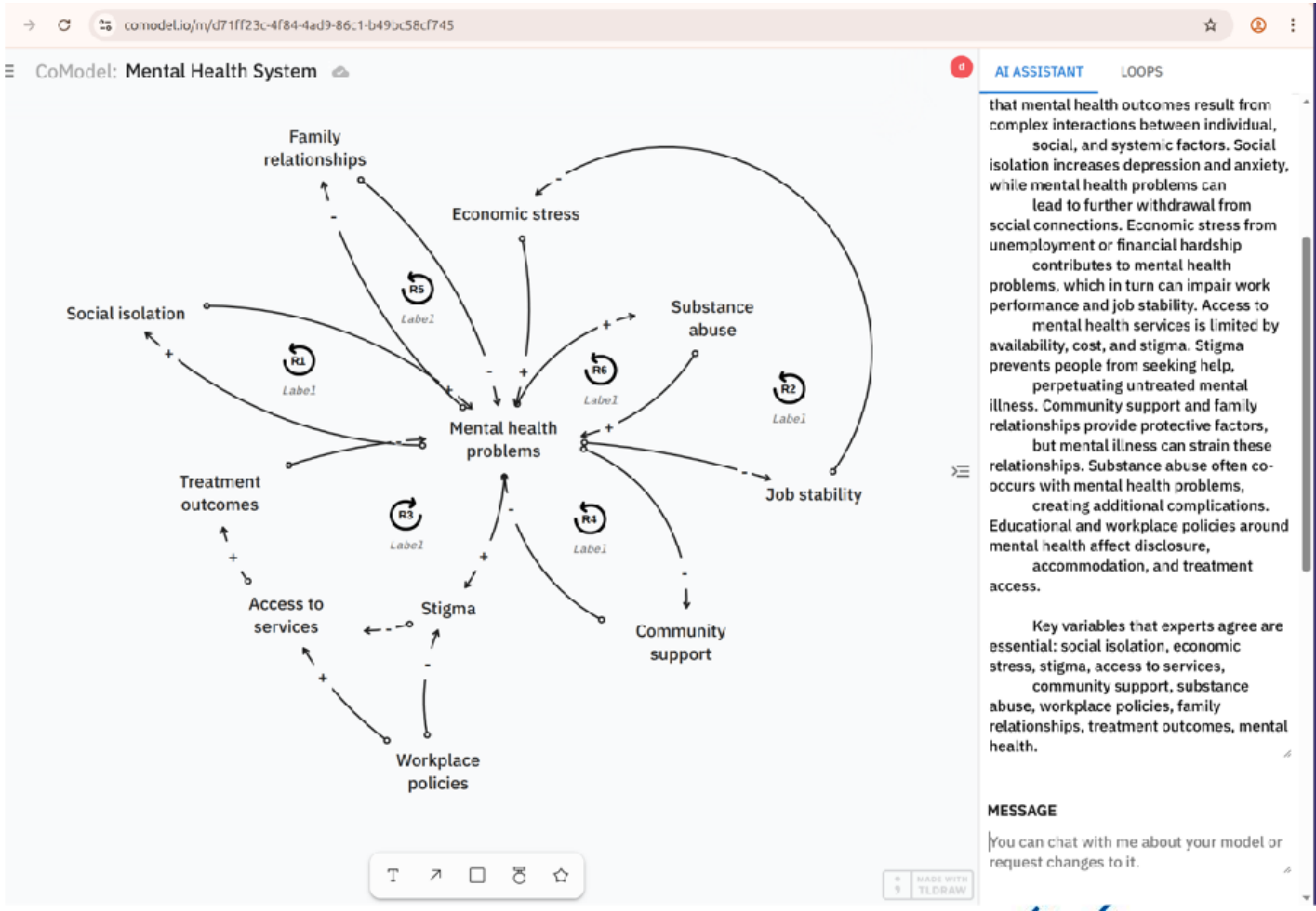
The mission of the BEAMS Initiative is to engage the AI and modeling communities in devising tests for how well AI and ML tools support the modeling process, so as to foster the development of more responsible and ethical tools.

Discussion board: groups.io/g/sd-ai



Explore Engines & Evaluations

ub-iad.github.io/sd-ai/



Thank you for listening!

I welcome comments, questions and suggestions

Download the model and ODD

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