Modeling Wildfire Evacuation with Embedded Fuzzy Cognitive Maps: An Agent-Based Simulation of Emotion and Social Contagion: The Overview, Design concepts, and Details (ODD) Protocol Document

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1 Overview

In what follows we provide a detailed description of the model based around the standard Overview, Design concepts, and Details (ODD) protocol proposed by Grimm et al. [13]. We provide this documentation in order to provide more details about the model and aid others in replicating and extending the model if so desired. The model itself is available at: `https://github.com/ozzyzhou99/LA-Wildfire-Model`, while Figure 1 shows the graphical user interface of the model. On the left-hand side one can see user-specified inputs along with model outputs. NetLogo 6.4.0 [32] was used to implement the model.

1.1 Research Purpose

This research develops an agent-based model of "wildfire evacuation and emotion coupling" to simulate the impact of emotional factors on residents" evacuation decisions during wildfire evacuations. The model focuses on three key issues: first, how do different income levels influence evacuation emotions? Are low-income groups more prone to making negative decisions? Research by Yabe et al. [33] indicates that income has a significant impact on evacuation capacity and choice, as low-income groups often face greater obstacles in accessing resources and transportation in emergency situations. Second, how does emotion (i.e., the states of calm-anxious-panic) spread through social contact networks, and what chain reactions do they trigger on individual decision paths and overall evacuation patterns? By integrating a customized A* path optimization algorithm with an fuzzy cognitive mapping (FCM) emotional propagation module, the model establishes a framework where individuals can respond in real-time to spatial layout and emotional contagion.

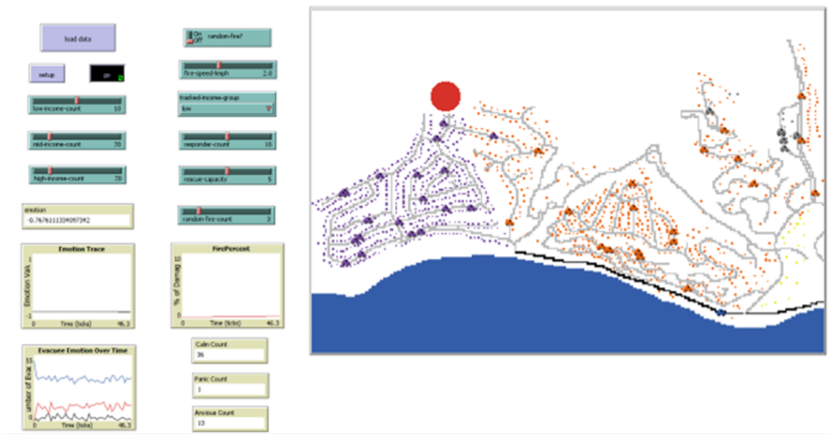

Fig. 1. Graphical User Interface of the Model

1.2 Datasets

This study integrates multiple datasets from public government platforms as the basis for modeling wildfire evacuations in the Los Angeles area as shown in Table 1. Due to differences in spatial resolution between different datasets, we minimized data inconsistencies by standardizing the coordinate systems and spatially stitching the datasets together. In this research, the household income data was obtained from the Median Household Income dataset published by the Los Angeles County Department of Public Health [18]. It provides information on median household income for 210 neighborhoods, which we used to construct proxy income categories. The housing data used the Damage Inspection (DINS) data provided by CAL FIRE [2]. This dataset documents damage to more than 10,000 structures impacted by wildfires in California in 2025. This dataset allows us to identify high-risk areas of LA and serves as a spatial layout for modeling wildfire evacuation. The road network data is derived from the Street Inventory provided by StreetsLA and is used to construct the accessible road network in the model, which is processed to form the spatial environment of the model to assign values to the attributes of subsequent individuals and to implement the wayfinding methodology [30].

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

1.3 Study Area

The simulation area is located in the Castellammare neighborhood of the Pacific Palisades, adjacent to The Getty Villa, in western Los Angeles, California. This area was damaged by the 2025 Los Angeles fires along the Pacific coast and related transportation arteries [26]. The area has been affected by wildfires many times in the past. As shown in Figure 2, it has a composite "coast-hill-city" topography, which is an ideal scenario for researching the interaction between coastline constraints, road bottlenecks, and fire. When importing data into the model, we first convert the houses, roads, and sea from high-resolution vector data to 10m x 10m raster data using ArcGIS Pro. Then we convert these rasters to ASCII format and import them into NetLogo. The initial fire source points are randomly sampled based on historical fire distribution patterns [3]. Figure 3 shows the data used to set up the model experiment, which are household income, house location, and road network data. The model time step was set to one second (1 tick). Since ∼94% of evacuees during wildfire evacuation choose to drive [35], considering the size of the study area and the speed at which cars move, 1s per tick allows us to observe the complete evolution of fire spread and panic propagation. This provides a visual basis for validating emergency response measures.

Fig. 2. Study area: A wildfire-affected community in Los Angeles in 2025 (Source: [12]).

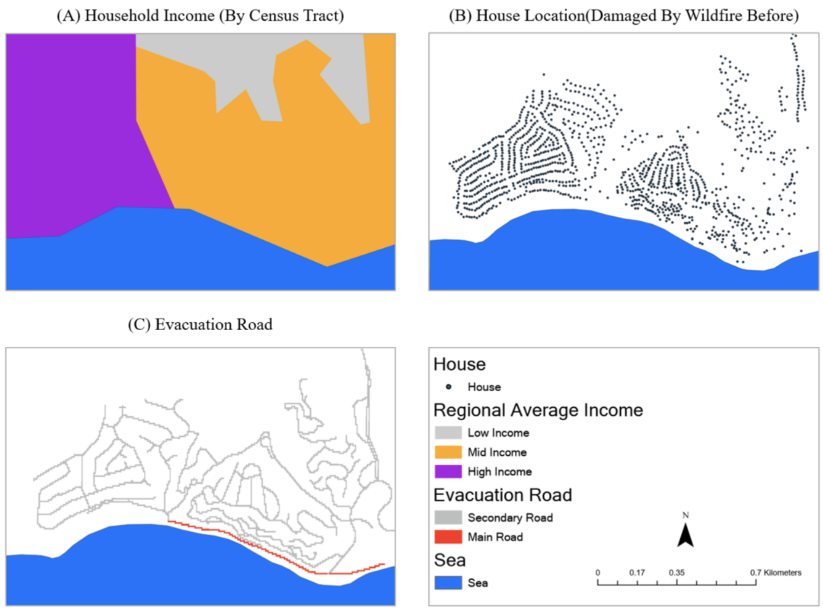

Fig. 3. Data used in the setting up the model experiment. (A) is household income data, (B) is location of previously affected houses, and (C) is evacuation road data.

1.4 Entities, State Variables, and Scales

This model comprises three main entities: evacuees, responders, and environmental grid cells (i.e., patches). Evacuees represent residents driving private vehicles, with core state variables including income level, emotion level, current behavior mode, and pre-generated travel paths and progress indices (evac-path, path-index) generated by the A* algorithm. Responders are designed to simulate police, fire, or other emergency personal, recording their current task mode (i.e., "rescue" or "evacuate"), number of people on board (rescue-count), and destination path (destination-path), among other variables, to dynamically switch between rescue and evacuation operations. We designed the rescuer here to insert a calm third party [21]. They affect the evacuee's mood. By making evacuees calmer, they are guided to make rational evacuation decisions. Each grid cell represents a 10 m $\times$ 10 m spatial resolution of roads, buildings, water areas, or exits, and carries attributes such as traffic resistance (travel-cost), fire status (is-fire?), and safe exit status (is-exit?), providing foundational data for path search and fire propagation. The unit size of 10m x 10m was selected because, according to the FHWA Road Diet Manual [9], this is equivalent to the typical cross-sectional width of urban roads. This allows a single cell to represent a road or a small building [9]. In addition to individual attributes, the model maintains several global control variables, such as fire front radius (fire-radius) and growth rate, emotional social contagion radius (social-radius), and its 3×3

contagion matrix (contagion-matrix), to drive spatiotemporal interactions across agents. Spatially, the research area covers a mixed coastal-hilly-residential zone in western Los Angeles. Temporally, 1 tick corresponds to 1 second, which can fully present the evolution of the disaster and the movement of people.

1.5 Process Overview and Scheduling

This model advances in a loop with a time step (tick) of 1 second. Each iteration sequentially executes four phases. First, the model expands the burning area based on the fire propagation speed and dynamically sets road pass ability. Next, it calculates and updates the emotions and behaviors of evacuees. Then, it schedules the search-rescue-evacuation process for responders. Finally, statistics are recorded, and termination conditions are triggered (all individuals safely evacuated, or 10,000 ticks reached). The two types of agents interact within the same spatial-temporal framework. Evacuees' behavior can alter road congestion and spread emotions among themselves, while the presence of rescuers in turn influences Evacuees' emotional states. Here, we use a fire spread model in which the fire spreads outward at a constant speed from the center of the fire. Since the focus of this model is not on fire spread, this simple method is used. The fire spread speed is set to the normal average speed of California fire in a light breeze, which is 2 km/h [29].

As shown in Figure 4, the evacuation process goes through three consecutive stages every tick. "Compute Emotion" is performed after the simulation starts. First, the "five factors" information at the individual level (income level, distance to the exit, distance to the main road, distance to the fire source, and social infection intensity in the previous round) is summarized, and the latest emotion value P is obtained through a function calculation. In rapidly evolving disaster scenarios such as wildfires, individual evacuation behavior is often driven by multiple factors, including risk exposure, accessibility, and social influence. These five factors can simultaneously capture four mechanisms that have been repeatedly identified in the literature as the most influential factors in evacuation success: differentiated vulnerability, spatiotemporal opportunity constraints, dynamic hazard exposure, and emotion/information diffusion [10, 24, 25, 31, 33].

The second step is "Update Behavior". The model uses soft-max mapping (see Section 3.2) to convert $\mathbf{P}$ into three behavioral states: Calm means that evacuees will evacuate rationally. Panic means that they will remain stationary. When the emotion is Anxious, evacuees will act in a disorderly manner. (See Section 3.2 for specific mapping formulas and parameters.)

Evacuees' behaviors are divided into three categories, corresponding to the three emotional states mentioned earlier. When evacuees are in the "Calm", they will follow the pre-planned shortest path (from secondary roads to main roads, following the evacuation guidelines provided by the LA government) to the nearest exit. When evacuees are in the "Panic", they will remain stationary due to extreme fear until the next emotion update changes their state. When evacuees are in an "Anxious", they move randomly within a local area and may inadvertently enter congested areas or fire zones. When evacuees reach an exit, they are considered safely evacuated and removed from the system.

Figure 4B shows the decision chain of rescuers. First, "Head Toward Fire Area". In a fire emergency response system, "moving against the flow" is the core responsibility of rescuers (firefighters, search and rescue personnel, etc.). The National Fire Protection Association (NFPA) explicitly states in NFPA 1140 that the primary objective of wildfire emergency operations is "to protect life and property," and defines "initial attack" as advancing toward the fire source [23]. Therefore, in this model, the first task of rescuers is to advance toward the fire source. When rescuers are in "rescue mode", they use A* pathfinding to navigate toward a fire scene. If they encounter a road blocked by new fire along the way, 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 one by one, 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. Simultaneously, the number of evacuees on board is checked (Reach Rescue Limit). Once the capacity limit is reached, rescuers switch to "evacuation mode". In "evacuation mode", the vehicle takes the fastest route to the exit, directly removing rescued individuals from the system; the vehicle is then removed from the scene to avoid causing traffic congestion.

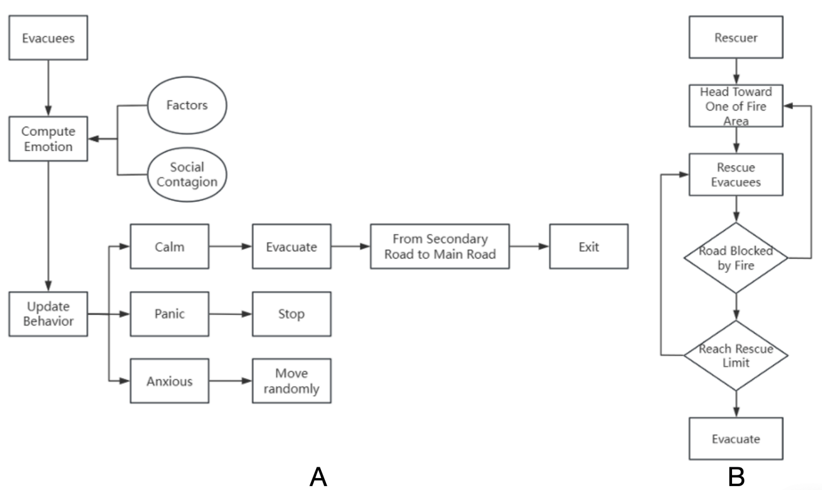

Fig. 4. Evacuees' Workflow (A), Rescuers" Workflow (B).

2 Design Concepts

The fundamental principle of this model is to embed a Fuzzy Cognitive Map (FCM) into a multi-agent evacuation framework to dynamically characterize emotion-driven decision-making. The "emotion level" output by the FCM is converted into an emotion state through a set of formulas. Emotional states control the actions of evacuees. Rescuers, as calm third parties, only influence the emotions of other evacuees through emotional contagion, while their own emotions remain calm. As local interactions accumulate, macro phenomena such as social emotional contagion and group evacuation and gathering emerge. The subjects themselves do not undergo long-term evolutionary learning but update their emotional levels at each tick based on the embedded FCM, reflecting short-term adaptive behavior.

2.1 Objectives

Evacuees reach the evacuation destination on the east side in the shortest possible time, which means that they will head east along Highway 1 to the shelter in LA. Rescuers rescue evacuees as much as possible within the rescue limit. Embedded FCM provides a fast and low-rational prediction. Emotional levels are calculated based on income, neighborhood panic, and spatial layout factors, and then mapped to individual behaviors. The model currently does not include long-term learning, and all weights are set based on other literature and experience. However, individuals make limited rational decisions by evaluating the fire intensity and congestion in the next N grid cells within the local road network, thereby reproducing the "bounded rationality" of real-world decision-making. Table 2 shows the variables in the model, their default inputs, ranges of variation, and their roles in the model.

2.2 Interactions

The perception range of the main entity is the extended Moore neighborhood: residents within a radius of 3 patches, rescue personnel within a radius of 5 patches. Researchers indicates that 30 meters in open, smoky wildfire areas is the typical range of perception for evacuees, while rescuers have a greater range of perception than evacuees [34]. The perceived content includes the extent of flames, road congestion, and the emotional states of nearby individuals. The main mode of interaction is social emotion contagion (see Section 3.2 for more details). There are two forms: contagion of emotional states between evacuees when they are close to each other, and contagion of emotions from calm third parties to surrounding evacuees. When agents in a certain area infect each other with emotions due to congestion and gather, they spontaneously form temporary groups. The emotions of these groups tend to become the same due to frequent emotional contagion and similar external factors. The default speed at which the fire spread is 3 km/h, which is the typical speed at which wildfires spread in California [8]. The speed of rescue personnel is based on the average speed of fire rescue vehicles of the U.S. Forest Service, which is 45–60 mph [20].

Table 2. 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

2.3 Heterogeneity and Stochasticity

The model explicitly depicts multiple heterogeneities. The different income levels of evacuees affect the fluctuations in their emotional levels. Due to differences in the types of transportation and evacuation experience, the movement speeds of rescuers and evacuees are not the same. Sources of randomness include: the location of wildfires in a multi-point wildfire pattern, the spread speed of wildfires, the choice of a particular fire source by rescuers to proceed with rescue operations, and the randomness of the mapping of individual emotional levels to emotional states.

3 Details

3.1 Initialization

The time step of this model is 1 second; the maximum duration is 10,000 ticks, which accounts for approximately 2.78 hours of simulated time, or until all-evacuated? = true. When initializing the spatial environment, the model loads in the road network, the locations of disaster-affected houses, the income level of each household, and the evacuation destination.

As noted above (Section 1.4, this model has two types of agents. Evacuees are randomly generated in three income levels based on house location, with n1, n2, and n3 evacuees assigned income levels. Rescuers enter the disaster-affected community along Highway 1 from the evacuation point. They will select a fire source to respond to in real time.

3.2 Sub-models

Social Contagion

Neighborhood selection:

$$N_i = \{k \mid dist(i,k) \leq R_s, k \neq i\}. \tag{1}$$

Only consider evacuees of the same type within a radius of R_s (5 patches in the model, approximately 55–60 m). This scale is derived from observational studies of wildfire evacuation: in smoke and noise environments, people are most sensitive to changes in group mood within 50 m [20, 27].

Distance decay weights:

$$w_d(k) = \frac{1}{1 + \mathrm{dist}(i,k)1} \tag{2}$$

The use of an inverse distance function avoids excessive effects from distant neighbors and is consistent with classical gravity decay models [6].

Emotional coupling matrix (ECM):

$$C = \begin{bmatrix} 0.1\ 0.2\ 0.3 \\ 0.4\ 0.1\ 0.5 \\ 0.2\ 0.3\ 0.1 \end{bmatrix} \tag{3}$$

The rows/columns are (calm, panic, anxious) in order; the values are derived from Mei et al.'s [22] experimental calibration of the contagion rate of group behavior and have been slightly adjusted in this study. The matrix allows for asymmetric effects: for the same panic, person-to-person is much stronger than "calm → panic", reflecting the psychological conclusion that negative emotions spread faster [15, 17].

Integrated social impact:

$$SI_i = \frac{\sum_{k \in Niwd(k)} C_{b_k b_i} p_k}{\sum_{k \in Niwd(k)} C_{b_k b_i}} \tag{4}$$

Numerator: Calculate the sum of the double-weighted (distance × infection coefficient) PK of all neighbors" emotions.

Denominator: The sum of the corresponding weights—normalized to ensure that SIi remains in the range [-1, 1] and does not shift from the baseline due to differences in the number of neighbors.

Emotional Updates (Embedded FCM)

$$p_i = \tanh\left(\beta_1 \text{ income }_i + \beta_2\left(1 - \frac{d_{\text{exit}}}{200}\right) + \beta_3\left(1 - \frac{d_{\text{road}}}{200}\right) + \beta_4\left(1 - \frac{d_{\text{fire}}}{200}\right) + \beta_5 SI_i \tag{5}$$

Equation 5 is responsible for converting values into a finite, interpretable emotional scale. Equation 5 can prevent linear combinations from becoming too large, causing "emotion values to spiral out of control" or numerical explosions. Dividing by 200 scales the original distance to the 0–1 range, which facilitates comparison between different scaling coefficients β and also means that distances beyond 200 patches have little to no effect on the emotional value (200 patches $\approx$ 2 km (Model 1 patch $\approx$ 10 m) [19, 20].

Each coefficient β was not arbitrarily assigned but informed by prior studies. Specifically, β_1 (income) follows evidence that socioeconomic status significantly affects evacuation behavior and emotional vulnerability [33, 16, 7]; β_2 (distance to exit) reflects that exit accessibility has impact on evacuation efficiency [31]; β_3 (distance to road) draws from studies on wildfire evacuation and road network characteristics [24]; β_4 (distance to fire) indicates the effect of distance from the fire source on an individual's sense of urgency to evacuate; the closer the fire source, the more likely the individual is to feel danger and evacuate early [20, 10]; and β_5 (social contagion intensity) is based on modeling of emotional contagion in crises [22, 21, 14]. These references provide empirical grounding for the FCM, while slight adjustments were made on coefficients to ensure stability within the simulation.

In Figure 5, we show how the input factors—household income level, distance to the destination exit, distance to the main road, and distance to the fire source. These factors first enter the box labeled "Convert emotion level to emotion," corresponding to Equation 5.

The arrows point to the central "Evacuees–Emotion" node, indicating that individuals receive a new emotion level Pi at each tick. The central and right-side groups of "Evacuees–Emotion" are connected by thick lines, illustrating "Emotion spreading among nearby evacuees." The circular 911–Calm node emits unidirectional arrows toward evacuees, representing the calming effect of rescuers on the crowd. Figure 5 visually integrates the submodel of social infection and emotion update in a closed-loop sequence: "Input factors $\rightarrow$ FCM calculation $\rightarrow$ individual emotions $\rightarrow$ social contagion loop."

Emotion–Behavior Mapping (Soft–max Decision)

$$\widetilde{\pi_{\text{calm}}} = e^{-\gamma p}, \widetilde{\pi_{\text{panic}}} = e^{\gamma(p-0.5)}, \widetilde{\pi_{\text{anxious}}} = e^{\gamma p} \tag{6}$$

$$\pi_j = \frac{\widetilde{\pi_J}}{\sum_k \widetilde{\pi_k}}, b_i \sim \text{ Categorical! } (\pi_{\text{calm}}, \pi_{\text{panic}}, \pi_{\text{anxious}}) \tag{7}$$

Soft-max ensures that the sum of the three probabilities is 1 and can be used to regulate the "decision steepness" $-\gamma$=3 is widely used to characterize rapid

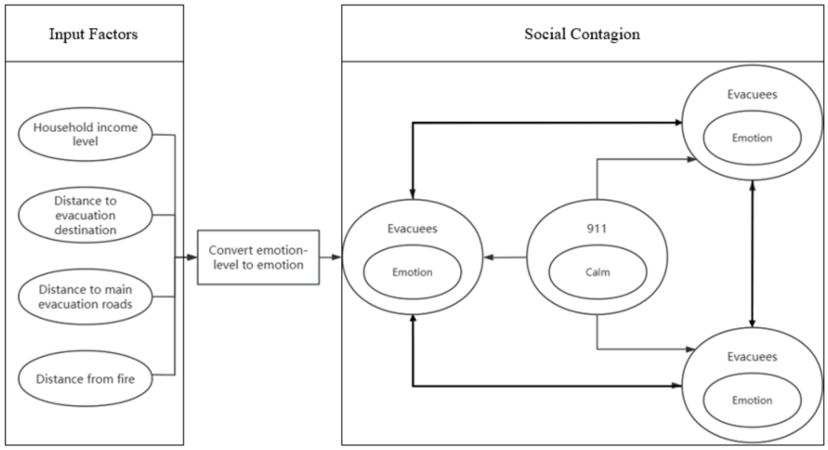

Fig. 5. Agent-level embedded FCM loop with social contagion.

attitude differentiation among people in stressful situations [11]. Smith et al. [28] regarded πcalm, πpanic, etc. as the posterior distribution of potential behavioral strategies in the active emotion inference model. This study directly borrows this idea and assigns continuous P to three discrete states (calm, anxious, panic) through soft-max[28].

The emotional value soft normalization and behavioral decision-making process are as follows: first, use Equation 5 to obtain the relative strengths of "calm / anxious / panic", then use Equation 6 to normalize them to probabilities, and the three π values will change with P; finally, use Equation 7 to obtain the final behavior through random sampling.

4 Model Verification

In this section we conducted code review and unit testing on the model. To ensure the model is verified, first, we review the NetLogo code line by line to verify variable naming and loop boundary settings. Then, unit tests with minimal input 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. We set the number of evacuated vehicles, fire spread speed, and FCM edge weights to 0 and their maximum theoretical values, respectively, to observe whether the model terminates stably without runtime errors. Using NetLogo's BehaviorSpace, we batch-ran different parameter combinations (e.g., the number of people in each income class, wildfire spread speed, and random wildfire count) and recorded the abnormal termination rate (currently 0%).

5 Model Validation

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

First, consider traffic congestion issues. Long-term monitoring data from the California transportation data (PeMS) shows that the intersections of Highway 1 and other secondary roads are most prone to sudden drops in vehicle speed during emergency evacuations [5]. Our simulations 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. Second, 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 [4]. 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.

Additionally, emotions influence individual behavior. We set up three monitors, each capturing the number of evacuees in a particular emotional state. Through these three monitors, we captured the number of agents exhibiting different behavioral patterns. We found that the number of agents in each of the three behavioral patterns updated at each tick. This indicates that our real-time emotional mapping model is successful. Based on the above comparisons, we conclude that the model has passed the Level 1 validity test. The model can reproduce traffic congestion patterns spatially. The social differences and emotion-behavior coupling are consistent with empirical studies. This validation ensures the model's reliability at the macro-level pattern. It should be noted however, that income groups differ in reality largely because of resource availability (e.g., transportation and housing). In our model, however, we abstract away from explicit resource distribution and focus on the role of emotional responses in shaping evacuation decisions of people under emergency conditions.

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