

# AGENT-BASED SIMULATION OF TSUNAMI EVACUATION USING PUBLIC BUSES IN PUNTARENAS, COSTA RICA

ESPINOZA HERNANDEZ Kristel Paola<sup>1</sup>

Supervisor: Erick MAS<sup>2</sup>,  
Shunichi KOSHIMURA<sup>3</sup>

## ABSTRACT

This study evaluates a tsunami evacuation strategy based on public buses for far-field tsunami scenarios in Puntarenas City, Costa Rica, under conditions without using private vehicles. Puntarenas is a low-lying coastal city built on a narrow sandbar with a single 30-meter-wide land access, La Angostura, making it highly vulnerable to tsunamis. An agent-based model was developed to simulate both pedestrian and bus evacuation, incorporating variables such as bus availability, stop locations, reaction times, and tsunami arrival times. Using demographic projections, official hazard maps, and road network data, 288 stochastic scenarios were analyzed. Results indicate that high evacuation success is achievable when early community response is paired with optimized bus deployment, particularly under the longer warning times of far-field events. These findings outline the need for risk education, efficient resource allocation, and strategic evacuation planning. The model offers actionable insights for disaster preparedness in Puntarenas and serves as a reference for other coastal cities at risk.

**Keywords:** Tsunami, Agent-based models, Bus-based evacuation, Evacuation Planning, Disaster Risk Management.

## 1. INTRODUCTION

Costa Rica, located on the Central American isthmus between the Pacific Ocean and the Caribbean Sea, lies along the Pacific Ring of Fire and near the active Middle American Trench (MAT), making it highly susceptible to tsunamis (Chacón & Protti, 2011). To mitigate this threat, Costa Rica has implemented a national monitoring and warning system, which incorporates information from international organizations such as the Pacific Tsunami Warning Center (PTWC) and the Caribbean Tsunami Warning System (CARIBE-EWS) (Chacon et al., 2021).

The study area, the city of Puntarenas, is a narrow sand bar in the Central Pacific formed by deposits from the Barranca River (Bergoeing, 2015) and rises only 2 m above sea level. It is connected to the mainland through a single 30 m-wide access point known as La Angostura, creating a critical bottleneck during evacuations. Combined with high population density and seasonal tourism populations, these conditions increase the risk of congestion, isolation, and delays in

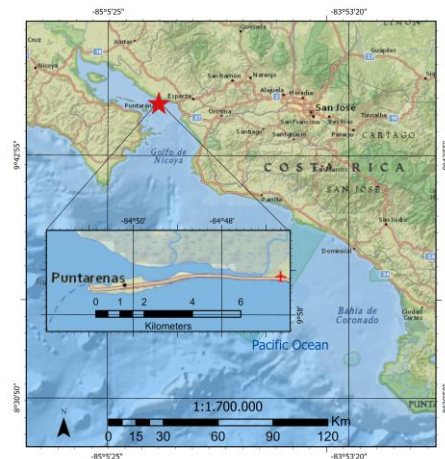


Figure 1. Puntarenas City Location

<sup>1</sup> SINAMOT Program, Physics Department, National University of Costa Rica.

<sup>2</sup> Associate Professor, International Research Institute of Disaster Science (IRIDeS), Tohoku Univ.

<sup>3</sup> Professor, International Research Institute of Disaster Science (IRIDeS), Tohoku Univ.

reaching safety. Given its topography, the entire city is considered at high risk for tsunami inundation (Zamora et al., 2012).

There is an urgent need to establish a contingency plan that includes both residents and tourists, identify evacuation routes, implement measures to minimize chaos and traffic congestion during evacuations, and educate the public on disaster preparedness and responses to ensure sustainable practices. The Municipal Emergency Committee (CME) has proposed using buses for evacuation in far-field tsunamis. Therefore, this research addresses the following objective: to evaluate the performance of a bus-based evacuation strategy for far-field tsunami scenarios without private vehicles, using an agent-based model for Puntarenas City, Costa Rica, with the aim of identifying conditions that maximize evacuation efficiency and enhance disaster preparedness planning.

## 2. DATA

For this study, four main datasets were used: road network, bus stops, population, and a far-field tsunami inundation scenario. The road network was extracted from OpenStreetMap (OSM), verified in the field, and subsequently converted into nodes and links for agent navigation. Official bus stop locations, provided by the Public Transport Council (CTP), were integrated into the same network layer to maintain connectivity consistency.

Population data come from the 2011 National Census at the UGM level, projected to 2024 using the Langford method (2007) and official INEC growth rates. The tsunami inundation scenario corresponds to a far-field magnitude Mw 9.4 event originating from the Tonga-Kermadec Trench (IOC, 2018), with an estimated arrival time in Puntarenas of 14 hours and flow depths between 0.09 and 5.28 m, as modeled by SINAMOT-UNA. All spatial datasets were processed and integrated into a single GeoJSON file to optimize the performance of the agent-based model in NetLogo.

La Punta (see Figure 2) has the highest population density and suffers from widespread flooding, with coastal areas exceeding 5 m deep and an average of 3 m across the entire sector. Bus stops are mainly located along the main road, ensuring coverage in both densely populated and sparsely populated areas. In contrast, La Angostura faces significant flooding and a critical risk of isolation, as it is the only land access to the mainland.

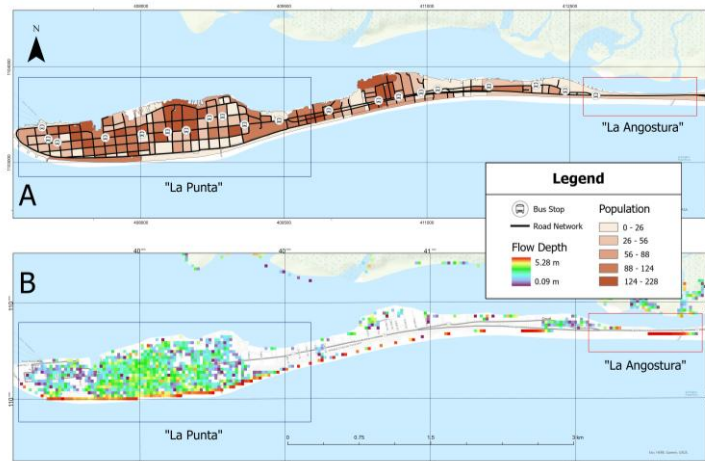


Figure 2. Input data layers used in the agent-based evacuation model for Puntarenas, Costa Rica. A: Population distribution, road network, and designated bus stops. B: Maximum tsunami inundation depth overlaid on the same area.

## 3. METHODOLOGY

### 3.1. Evacuation Model

The Puntarenas evacuation model, PUNTA-EVAC, is an adaptation of TUNAMI-EVAC, originally developed by Mas (2012). It simulates the evacuation dynamics of both pedestrians and buses in Puntarenas, aiming to assess the feasibility of evacuating over 8,000 residents and 25% of the tourist capacity by integrating pedestrian routes with public transportation. The model and its source code are openly available on GitHub: <https://github.com/kristelspinozah17/PUNTA-EVAC>.

### 3.2. Simulation Logic

The simulation integrates shortest-path algorithms, probabilistic reaction times, and predefined behavioral rules to represent how individuals respond during a tsunami. Agents react based on various scenarios that reflect differences in response speed and preparedness.

#### 3.2.1. Network Routing: Dijkstra Algorithm

Dijkstra's algorithm is one of the most widely used methods for finding the shortest path between nodes, introduced by Dijkstra (1959). It is commonly applied in transportation and evacuation models. This algorithm identifies the most efficient route with the lowest total cost from a starting node (node A) to one or more destination nodes. The formula for Dijkstra's algorithm is as follows:

$$d[u] = \min(d[v], [u] + w(u, v)), \quad (1)$$

where  $d[u]$  represents the shortest known distance from the origin node  $s$  to the node  $v$ , while  $d[v]$  is the shortest distance already calculated to the neighborhood node  $u$ . The term  $w(u, v)$  denotes the weight or cost of the path between the nodes  $u$  and  $v$ . The operation  $\min$  indicates that the smallest value is between the current distance and the new possible route passing through  $u$ .

#### 3.2.2. Reaction Time: Rayleigh Distribution

Reaction time refers to the interval between when an official tsunami warning is issued and when an individual begins their evacuation. In the case of a far-field tsunami, this lead time may span several hours. This factor is vital for the success of evacuation efforts (Makinoshima et al., 2020). In this research, the reaction time will be modeled using the Rayleigh distribution to capture the variability in how different individuals respond to tsunami alerts.

The Rayleigh distribution is a density function that effectively represents positive reaction times, showing a single mean that indicates the most likely time for people to begin evacuating. Its cumulative density function (CDF) is:

$$f(x; \mu_{mean}) = 1 - \exp\left(-\frac{\pi x^2}{4(\mu_{mean})^2}\right), \quad x \geq 0. \quad (2)$$

where,  $x$  represents the reaction time in minutes, while  $\mu_{mean}$  is the mean reaction time and is a parameter that controls the spread of the Rayleigh distribution and reflects the average behavioral delay in the population.

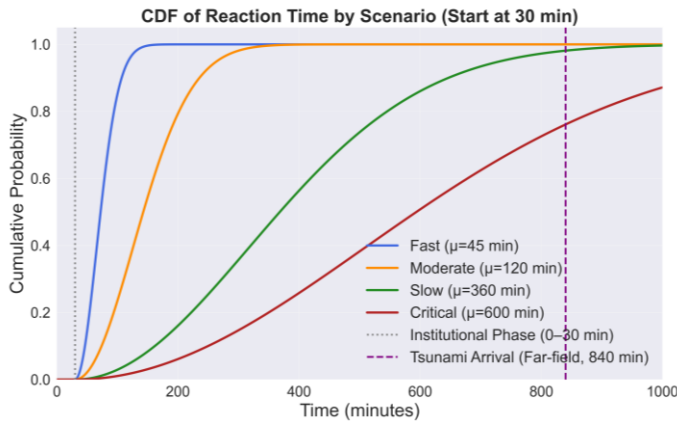


Figure 3. CDF of Reaction Time Scenarios

For this model, we established four scenarios for reaction times. In the case of a distant tsunami with an 840-minute + warning period (30 minutes for evaluation and alert issuance), both the Fast and Moderate scenarios yield a nearly 100% probability of reacting before the tsunami strikes. The Slow scenario would allow about 90%, while the Critical scenario would result in an effective response rate of only about 60% (see Figure 3).

### 3.3. Agents' Behavior During the Evacuation

The model simulates evacuation with two population groups: residents and tourists, both able to walk or board buses depending on proximity to stops and available capacity. Walking speeds follow a normal distribution, averaging 1.34 m/s, with variation to reflect slower and faster individuals. Residents start from their MGUs, while tourists begin at the “Paseo de los Turistas.” Buses, regulated by the Public Transport Council, operate at an average speed of 40 km/h (11.11 m/s) and have capacities of 40-80 passengers. In the simulation, buses run continuous cycles between stops and a shelter, testing different configurations to evaluate public transport’s effectiveness in reducing tsunami risk in Puntarenas.

### 3.4. Simulation Scenarios

The simulation evaluates 288 stochastic scenario combinations generated from seven variables: number of buses (5,10,20), bus capacity (40,60,80 passengers), reaction time (45, 120, 360, 600 min), bus stop distribution strategy (near-to-far or far-to-near), waiting time at stops (2, 5, 10 min), tsunami arrival time (840 min, far-field), and tourist volume (25% capacity). Tourist presence is set at 4,647 visitors, following Fruin's (1971) Level of Service category A (4 m<sup>2</sup> per tourist). Simulations were run in parallel on a Mac Studio (2022) with an Apple M1 Ultra, executing 10 runs per scenario, each covering 21,600 simulated minutes.

## 4. RESULTS AND DISCUSSION

To ensure the robustness of the tsunami evacuation simulation results, a convergence and variability analysis was conducted across the 288 stochastic scenarios. The coefficient of variation (CV) was used as the main stability metric, following the criteria of North & Macal (2007) and Lee et al. (2015). Scenarios meeting both operational efficiency ( $\geq 90\%$  evacuated) and statistical reliability ( $CV \leq 10\%$ ) were identified as high-performing candidates. This approach allowed us to distinguish between configurations that were both effective and consistent, and those whose variability limited operational applicability. The following section examines the best- and worst-performing combinations in detail.

### 4.1. Best performing scenarios

Convergence and variability analysis identified a group of high-performing scenarios, with near-complete evacuation and low variability between simulations. Of these, ten scenarios that achieved 100% evacuation were examined in detail to understand how behavioral factors such as reaction time and logistical resources, including the number and capacity of buses, interacted to produce successful outcomes.

The heat map visualization (Figure 4) revealed two main strategic patterns: one emphasizing rapid mobilization with short reaction times (45 min) and maximum bus deployment (20 buses), and another leveraging longer reaction times with high-capacity buses (60-80 passengers) and minimal wait times.

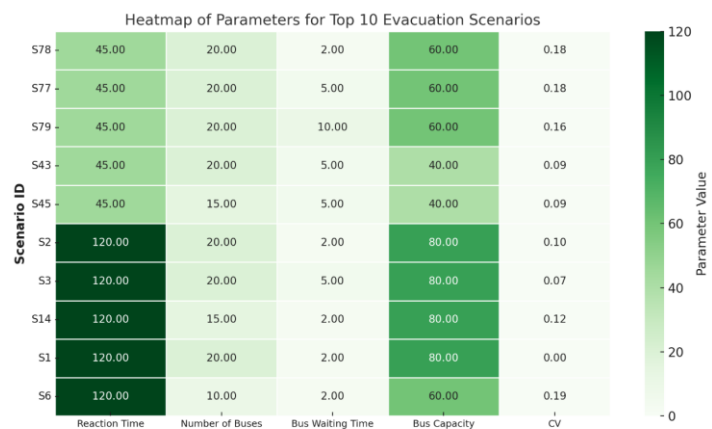


Figure 4. Top 10 scenarios: Main parameters

Performance metrics showed that in rapid response scenarios, evacuees reached safety within a timeframe of 290 to 430 minutes (see Figure 5). The operational reliability of the system demonstrated effective coordination and transportation infrastructure. This suggests that both rapid response strategies and advanced planning strategies can be effective as long as they are supported by adequate infrastructure and efficient coordination.

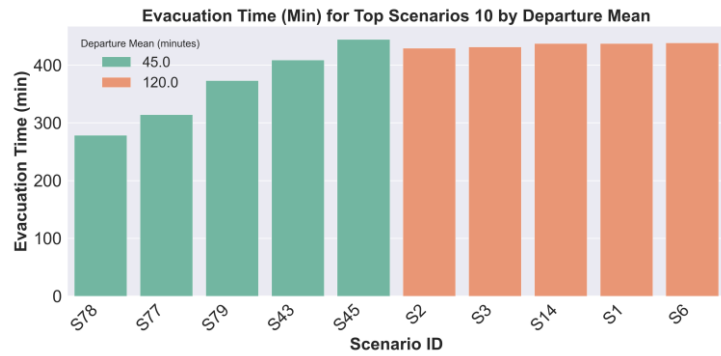


Figure 5. Top 10 scenarios and their evacuation time

#### 4.2. Worst Combination Scenarios

A sensitivity analysis was conducted to evaluate how four parameters (reaction time, number of buses, bus capacity, and wait time) affect evacuation performance. The results indicate that reaction time and number of buses are the most influential factors, with a significant impact on both the percentage of evacuees and the total evacuation time. Shorter reaction times and larger fleets consistently produced higher evacuation rates, while departure delays or limited vehicle availability dramatically reduced performance (see Figure 6).

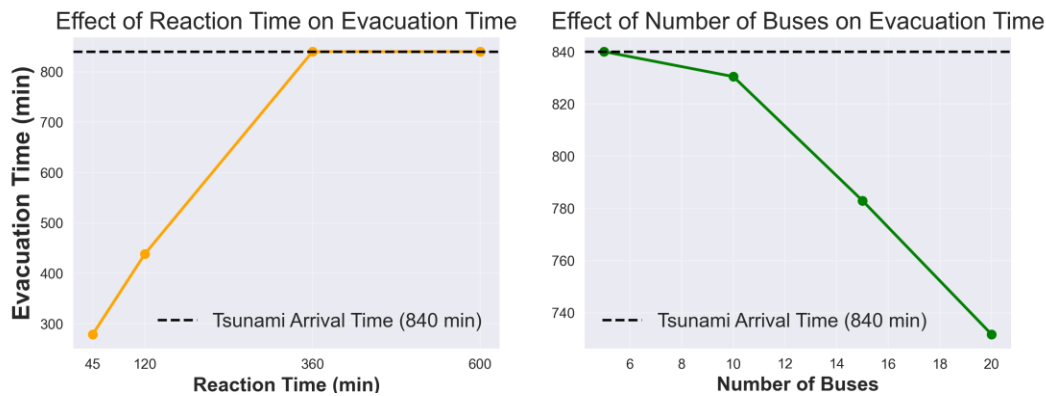


Figure 6. Effect of the reaction time and number of buses on the evacuation time

While bus capacity and wait time also influenced the results, their effects were less pronounced. Higher-capacity buses and shorter wait times tended to improve efficiency but failed to fully offset the negative impact of long reaction times or insufficient buses.

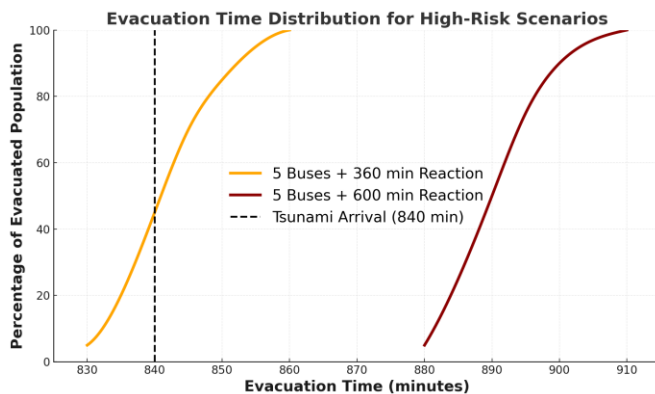


Figure 7. Percentage of evacuees for high-risk scenarios

In extreme cases, such as a 600-minute reaction time combined with only five buses (Figure 6), no simulation managed to evacuate the population before the tsunami arrival threshold of 840 minutes. These findings emphasize the need to prioritize rapid community mobilization and ensure sufficient transportation availability in tsunami evacuation planning. Even with optimal logistics, delays in initiating evacuation can make the operation unfeasible, underscoring the importance of

early warning systems, public awareness, and regular drills to reduce reaction times and improve operational reliability. These findings support the notion that evacuation time should not be analyzed solely based on averages but also on its variability and accumulated behavior, especially under critical conditions.

## 5. CONCLUSIONS

The results show that reaction time and transportation capacity are the most determining factors for evacuation success. Scenarios with an early response time of 45 to 120 minutes, combined with sufficient fleets and high-capacity buses, were able to evacuate 100% of the population. However, performance does not depend on a single parameter, but on the simultaneous coordination of multiple factors such as the number of buses, their capacity, and waiting time at bus stops. Poor combinations of these elements can reduce evacuation to less than 30% before the tsunami's arrival.

Furthermore, it was observed that the scenarios with the highest evacuation rates did not always coincide with the most stable ones, highlighting the need to balance efficiency and operational reliability. In this regard, planning must integrate functional early warning systems, efficient transportation logistics, and community participation and preparedness, in accordance with the Sendai Framework, to ensure more realistic, equitable, and sustainable evacuation strategies.

## ACKNOWLEDGEMENTS

I am deeply grateful to Dr. Erick Mas for his dedicated guidance, constructive feedback, and valuable insights that greatly contributed to the development of this research. I also thank Dr. Shunichi Koshimura for his warm reception and academic support during my time at Tohoku University. My appreciation is also extended to the IISEE staff for their continuous support and assistance, and to Dr. Shibasaki for his encouragement and advice throughout the program.

## REFERENCES

- Bergoeing, J. P. (2015). *Geomorphology of Central America: A syngenetic perspective*. Elsevier.
- Chacón-Barrantes, S. E., & Protti, M. (2011). *Journal of South American Earth Sciences*, 31(4), 372-382.
- Chacón-Barrantes, S., Murillo-Gutiérrez, A., Rivera-Cerdas, F., & Rossel, B. A. (2021). *Ocean and Coastal Research*, 69(suppl 1), e21039.
- Charnkol, T., & Tanaboriboon, Y. (2006). *IATSS research*, 30(2), 83-96.
- Dijkstra, E. W. (1959). *Numerische Mathematik*, 1(1), 269–271
- Intergovernmental Oceanographic Commission. Wellington, New Zealand, 29 October–3 November 2018.
- Lee, J.-S., Filatova, T., Ligmann-Zielinska, A., Hassani-Mahmooui, B., Stonedahl, F., Lorscheid, I., ... & Jakeman, A. J. (2015). *Journal of Artificial Societies and Social Simulation*, 18(4), 4.
- Makinoshima, F., Imamura, F., & Oishi, Y. (2020). *Progress in Disaster Science*, 7, 100113.
- Mas, E. (2012). TUNAMI-EVAC1: Tsunami evacuation model in NetLogo for Arahama, Sendai [NetLogo model]. GitHub. <https://github.com/erick2307/TUNAMI-EVA>
- North, M. J., & Macal, C. M. (2007). Oxford University Press.