A HYBRID APPROACH TO PEDESTRIAN EVACUATION MODELS

by

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Abstract

This work presents a hybrid pedestrian evacuation model (PEM) that provides insight on the vulnerability of Rincón to tsunamis by combining anisotropic least-cost-distance and agent-based approaches. This PEM relaxes certain assumptions often found in a PEM (e.g. constant evacuation speed, all individuals evacuate immediately). This work advances the PEM literature by improving upon the population distribution, assigning evacuation responses based on the predictions of a model fitted on stated responses, and penalizing evacuation times using a fatigue factor and reaction times. The results of this PEM can assist emergency managers in the evaluation of mitigation strategies by providing realistic evacuation scenarios with travel time evacuation maps and paths to safety and a sensitivity analysis of the different evacuation scenarios. Using the worst-case scenario, 33.97% of the population of Rincón reached safety under 5 minutes, 41.49% took between 5 and 15 minutes, and 24.53% took over 15 minutes.

RESUMEN

Este trabajo presenta un modelo de desalojo peatonal híbrido (PEM, por sus siglas en inglés) que ilustra la vulnerabilidad de Rincón a tsunamis, combinando distancia anisotrópica ponderada y modelos basados en agentes. El modelo propuesto relaja múltiples presunciones presentes en otros PEMs (e.g. velocidad constante, todos desalojan inmediatamente). Este trabajo mejora la distribución poblacional, asignando respuestas de desalojo basadas en entrevistas a la población de interés y penalizando tiempos de desalojo utilizando un factor de fatiga y tiempos de reacción. Estos resultados pueden ayudar a crear estrategias de migración, proveyendo múltiples escenarios con mapas de tiempo y rutas de desalojo y su respectivo análisis de sensibilidad. Utilizando el peor de los escenarios se obtuvo que el 33.97% de la población de Rincón alcanza zonas seguras en menos de 5 minutos, mientras que 41.49% tarda de 5 a 15 minutos y 24.53% tarda más de 15 minutos.

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GLOSSARY OF TERMS

ABM	Agent Based Model
ACS	American Community Survey
ALCD	Anisotropic Least Cost Distance
ATT	Anisotropic Travel Time
DEM	Digital Elevation Model
FT	Fatigue time
LULC	Land Use Land Cover
MA	Multi-Agent
PEA	Pedestrian Evacuation Analyst
PEM	Pedestrian Evacuation Model
PES	Pedestrian Evacuation Simulation
PR	Puerto Rico
PRSN	Puerto Rico Seismic Network
RT	Reaction Time
TEZ	Tsunami Evacuation Zone
TTT	Total Travel Time

1 Chapter –Introduction

Scientific advancements have made it a long way in a short period of time. Not even a hundred years ago, it was a dream for men to set foot on the moon, and today, a rover is exploring on Mars. But even with all these scientific advancements, there are still many things that humans have come to understand but have no power to stop. Hurricanes, tornadoes, hail, flash floods, earthquakes, and tsunamis are just a few of the phenomena humans are powerless against. The only thing we can do is to learn, respect, and prepare for them. On a humanitarian scale, it is important to help people recover, but preparing accordingly and setting up all the security measures can greatly reduce the impact of these natural disasters, and hence reduce humanitarian efforts. Part of this preparation on a macroscale involves being able to measure the at-risk population and set procedures that will help maximize the number of people to reach safety in case of a natural disaster. "Enhancing disaster-risk reduction before a disaster occurs, and also during the reconstruction process, requires enhanced knowledge regarding the most vulnerable groups, the areas at risk and the driving forces that influence and generate vulnerability and risk" (Birkmann, 2006). In summary, it is important to know how vulnerable is a specific population, the risks they face, and their ability to recover after a natural disaster.

In the case of a tsunami, the many great disasters can be traced as far back as 6225 B.C. The most recent ones (e.g. 2004 Indian Ocean, 2006 Java, 2009 Samoa, 2010 & 2015 Chile, 2010 Sumatra, 2011 Japan) have raised global awareness of tsunami hazards (Wood & Schmidtlein, 2011). The 2011 East Japan Tsunami killed 15,884 people and injured 6,147 people. Over 2,636 people were still missing as of February 10, 2014, and 94.5% of the total death count is attributed to drowning. Only 1.2% of fatalities were caused by the earthquake, whereas the remaining fatalities were caused by fires, landslides, and disease (Yeh, 2014). It is worth noting that in the case of Japan, thousands of lives could be saved thanks to the preparedness level. Chile is another example of how better mitigation and preparedness can help reduce the fatalities caused by earthquakes and resulting tsunamis. Although similar statistics can be anticipated for similar tsunami events in Puerto Rico, it should be noted that the outcomes will always depend on the size of the natural disaster and the level of preparedness.

Pedestrian evacuation models (PEM) can be used to better understand how the population can escape an at-risk area. Researchers have performed extensive pedestrian evacuation modeling and applied different approaches from those that assume the effort to travel uphill is the same as traveling downhill (isotropic) to approaches that assume traveling uphill is more strenuous (anisotropic). There are also approaches that assume that all individuals behave the same in the event of an evacuation (LCD) and those that more accurately depict that different individuals will assume different responses in the event of an evacuation (agent-based models). Yet, even with all these great advances, there are still many aspects of PEM that need to be looked at.

This work will describe the design and implementation of a PEM for Rincón, Puerto Rico–a major touristic destination for the Caribbean island. This city presents a real challenge for the residents and employees to reach safety in case of a tsunami. Many of the critical infrastructures, such as hospitals, are inside the flood zones. Past historical tsunami data, along with current tsunami flood models indicate that after the onset of a local event (e.g. earthquake, landslide), the first tsunami wave can arrive as early as in 5 minutes. There is very little anyone can do unless individuals already know how to evacuate and react promptly (Mercado & McCann, 1998).

There are many programs already in place preparing the population in case of a disaster. TsunamiReady®, sponsored by National Oceanic and Atmospheric Administration (NOAA), for instance, aims to help and recognize communities which have taken specific actions to be better prepared to face a tsunami event. The Caribe Wave exercise creates yearly scenarios of strong earthquakes generating a tsunami and encourages communities to practice their evacuation process and other response measures. Although these programs are very useful for the mitigation of the municipality and population, they are still being limited and do not provide insight on the potential damages that the at-risk area population is facing.

This work intends to go some steps further by providing insight on microscopic level of crowd evacuation in Rincón. The results of this simulation will provide an estimate on the number of people and families that might not be able to reach safety in case of a tsunami. Such analyses were developed using the delimited tsunami evacuation zones (TEZ) created by the Puerto Rico Seismic Network (PRSN) and the Department of Marine Sciences at University of Puerto Rico at Mayagüez (UPRM). The proposed model is a hybrid approach that combines practices in anisotropic least-cost distance (ALCD) and agent-based models to relax multiple assumptions commonly found in PEMs.

The literature covering the topic of PEM is extensive, but the goal of this work is to provide a tool to accurately estimate the time it will take for the population to reach safety. While many PEMs randomly distribute the total population count across the study area, the distribution of the population in this work is strictly based on Census and American Community Survey (ACS) tables. Such distribution further allows the model to incorporate attributes of the population (e.g. age, gender, dependent population) and treat them as diverse agents within the PEM.

Also, while many PEMs fail to simulate group-based evacuation, it is expected that members of the same household will evacuate together and not leave family behind (Fraser et al., 2013). This work considers group-based evacuation in the form of groups of individuals that share a household. These groups are also created following closely the population count and their attributes in the Census and ACS data. For the purposes of the proposed PEM, these groups are treated like families and, hence, often configured as a female and male partner sharing one or more children. Another issue that commonly arises in group-based evacuation and considered within the proposed approach is the fact that the speed of the slowest member of the group dictates the evacuation speed of the group.

On the other hand, it is fair to assume that not all individuals evacuate at the same pace. Some will be able to do it running; others might not even be able to walk. Thus, the proposed model uses an individual's age and gender to determine the pace at which the individuals will evacuate in the event of a tsunami. This assessment was based on the work by Hernández et al. (2017), where sports-event data from a local race was used to determine the groups that travel at approximately the same speed, so that each individual in any given group could be assigned a running speed using a probability density function (PDF).

The speed parameters obtained from the work by Hernández et al. (2017) were used as an input to calculate the anisotropic time with the r.walk algorithm (Fontanari et al., 2015). Once the anisotropic evacuation times were obtained, they were post-processed using two different penalties: one for reaction time and one for fatigue factor. For individuals traveling long distances, the fatigue factor penalizes evacuation times based on the distance traveled. The rationale behind this penalty is that as the distance traveled increases, individuals are going to experience fatigue and their evacuation speed is going to be reduced, accordingly.

Lastly, the proposed PEM further relaxes the assumption that all individuals evacuate at the same time and as soon as they perceive the signals of a threat by giving each agent its own evacuation response. In the proposed work, a survey on a sample of residents and tourists of

Rincón, PR was carried out to better understand evacuation responses at the individual level. Using the collaborative work by Dávila et al. (2017), evacuation responses were assigned to the population according to their attributes using a machine-learning-based prediction model.

After all, this work aims to increase the number of people that reach safety in the event of a tsunami by: (1) improving the population distribution, (2) assigning custom evacuation speeds and responses, and (3) introducing evacuation time penalties for fatigue factor and reaction time. In the process of addressing this aim, a custom geo-referenced inventory of residential, apartment complexes, commercial locations, critical, essential, and public infrastructure was developed to allow for a more accurate depiction of the initial location of the population and the natural boundaries and structures restricting their evacuation path. Accomplishing this aim will help provide valuable insight to Rincón mitigation officials on the different areas of Rincón where population will not have enough time to evacuate. It will further allow emergency responders and other related public officials to estimate the number of casualties in a variety of scenarios.

2 Chapter- Literature Review

This section provides a brief review of the literature related to each of the components of the proposed project. These components include: anisotropic least-cost distance, group pace estimation, evacuation responses, reaction, and fatigue model.

The subject of pedestrian evacuation in case of a natural disaster is very sensitive and important because of the number of peoples' lives that are at stake. The fact that most natural disasters are unpredictable and disastrous it makes it hard for communities to plan accordingly, since scientists can never pinpoint exactly where the next occurrence will be. The best way to minimize the effects of the disasters is with proper mitigation measures and have an evacuation protocol in place. Therefore, the government must prepare for all the possible scenarios. It would be impossible to create real evacuation exercises for every scenario, nonetheless, it is still of importance to understand and estimate the possible impact on the city's infrastructure and human life. This is where simulating pedestrian evacuation using specialized software is valuable. There has been a tremendous amount of studies to model pedestrian evacuation (e.g. Wood & Schmidtlein, 2011; P. C. Tissera et al., 2012; Sarmady et al., 2008; Ishida et al., 2013). Software modeling is crucial because it is impossible to create an actual evacuation scenario in a laboratory setting with thousands of people, especially when stress and panic are factors influencing an individual's reaction.

In Tissera, Printista, & Errecalde (2007), it is mentioned that the models used to simulate pedestrian evacuation can be categorized in *macroscopic* and *microscopic* approaches. Macroscopic approaches are based on differential equations that take into account the similarities with dynamics of fluids systems in the literature (P. C. Tissera et al., 2012). By nature, this type of model does not consider individual characteristics and neither local coordination problems (e.g.

collisions). This implies that the resulting models are often not flexible enough to fully understand the dynamics that arise in a pedestrian evacuation process. Macroscopic simulations deal only with general properties of the entire crowd such as flow, density, and speed. These models do not consider interactions of individual pedestrians with the environment and other pedestrians and, instead, use the relation of density to walking speed and flow to calculate overall movements of the crowd (Sarmady et al., 2008).

Microscopic models, on the other hand, try to replicate each individual reaction, which when put together generates the crowd evacuation simulation (Dijkstra & Timmermans, 2002). These models allow for more control over the different agents and, therefore, are more precise in replicating human behaviors. There exist various microscopic models but the scope of this work will be to extract features from ALCD and MA approaches to model pedestrian evacuation using the characteristics of the at-risk population in Rincón, PR. The combination of these elements will allow for a correct representation of the evacuation terrain and slopes, Census and ACS based household family distribution (U. S. Census Bureau, 2015), group-based evacuation speeds, and the effects of reaction delay and fatigue on the evacuation time.

2.1 Anisotropic Least-Cost Distance (ALCD)

Distance maps use least cost distance (LCD) algorithms to find the shortest path out of a hazard zone to safety. The hazard zone can be any area that represents danger such as a flood zone or tsunami evacuation zone. Wood and Schmidtlein (2011) used ALCD approach to generate maps that indicate the time it will take the population inside a flood area to evacuate to safe areas. The LCD approach uses geographic information systems (GIS) tools to calculate the shortest path to safety for every cell inside the flood area. An anisotropic LCD model (slower travel time uphill vs. faster travel time downhill) focuses on a path distance modeling approach that incorporates travel directionality, multiple travel speed assumptions, and cost surfaces that reflect variations in slope and land cover (Wood & Schmidtlein, 2012).

2.1.1. Pedestrian Evacuation Analyst (PEA) Tool

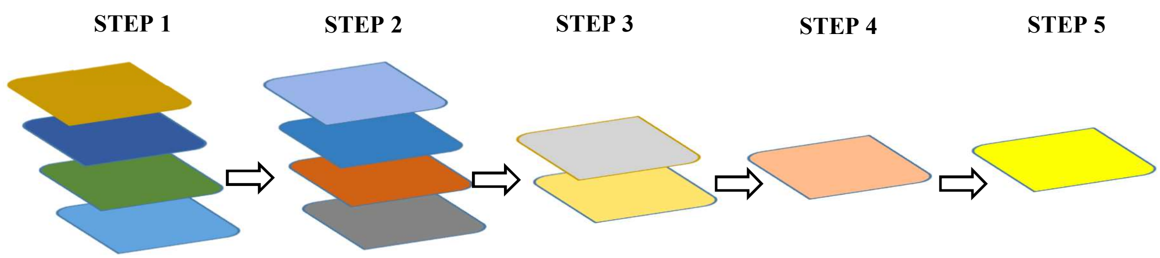
The Pedestrian Evacuation Analyst (PEA) software by Jones et al., (2014) implements this anisotropic path-distance approach, specifically designed for pedestrian evacuation from sudden-onset hazards, more specifically in the context of local tsunami threats. According to Jones et al., (2014), the model estimates evacuation potential based on elevation, direction of movement, land cover, and travel speed and creates graphical representations of the number of people that can reach safety at different time intervals. The tool allows to evaluate different speed scenarios, from slow walk (1.1 m/s) to fast run (3.83 m/s). Please refer to Table 2-1 for more information on the slow and fast walking speeds used in this PEM.

Table 2-1 Walking and running speed default values. User has the option to modify or add more values.
Source: **(Jones, Wood, & Peter, 2014)**

Travel-Speed Name	Travel-speed value (Meters/second)
Slow Walk‡	1.2
Fast Walk‡	1.52
Slow Run†	1.79
Fast Run†	3.85

For the areas where the model shows that the population will not be able to reach safety before the tsunami arrival time, the tool allows to incorporate vertical evacuation in the model. Policy making based on evaluation of vertical evacuation structures (VES) can help save a potentially large fraction of the at-risk population that otherwise would have no chance to reach safety.

PEA provides the user with a step-by-step workflow to use in ArcGIS software. The different files required to run the model and the tool layout in ArcGIS software are shown in Figure 2-1. Before using PEA, the user must first gather all the necessary files to run the model. Once all the required files are gathered, the user can prepare the digital elevation model (DEM), land use/land cover (LULC), and hazard zone files to use in the software.



[1A] ***i*:** Digital Elevation Model (Raster Vector)
[1B] ***i*:** LandUse/Land Cover
(Raster or Vector)
a. *Base Land Cover*
b. *Water*
c. *Roads*
d. *Buildings*

[2A] ***o*:** Path Distance Calculation (Vector)
[2B] ***o*:** Evacuation Surface Creation
[2C] ***p:*** Setting Maximum Time Value
[2D] ***o*:** Time Map Creation

[3A] ***i*:** Vertical-Evacuation sites process (Vector)
[3B] ***p*:** Merge Safe Zones

[4A] ***i*:** Incorporate Population Data (Vector)

[5A] ***o*:** Charts and Graphs

Figure 2-1 Workflow of the pedestrian evacuation analyst tool (PEA). The input (i), output (o) and processing steps (p) layers for each step is shown in the caption.

The DEM is the layer that contains the digital model of a terrain's surface or slope. The user has the option of entering both DEM raster and vector study-area files or only a DEM raster file. If only the DEM file is used, the software will use its projection as the projection for the scenario, and the DEM outline is the study area. If a study area is provided along with the DEM; therefore, the DEM (in same projection as the study area) will be clipped to the study area. After inputting the necessary files, PEA can now run the model within the ArcGIS 10.1 program. At this point, the user can start using the pedestrian evacuation tool by following the step-by-step procedure that is described next.

Step 1 is to input the four layers that will represent the study area. The first layer is the DEM layer. The better the resolution of this layer, the more precise the results will be. The second layer is the LULC, which is made of a combination of sub-layers such as type of terrain, waterways, houses and buildings, road network and so on. For each sub-layer, the user must specify the speed conservation values (SCV) that represent the fraction of a maximum speed that could be achieved across the given land-cover type as shown in Table 2-2 (Jones et al., 2014; Soule & Goldman, 1972; Wood & Schmidtlein, 2012). Jones et al., (2014) used the "hiking functions" formula described in Tobler, (1993) and converted the resulting speeds SCVs by dividing them by the maximum potential walking speed:

$$\boldsymbol{Walking\ speed} = \mathbf{6e - 3.5 * abs(slope + 0.05)}, \qquad (2\text{-}1)$$

where: *slope* refers to the inclination of the land as provided in the DEM layer, and *abs* refers to absolute value.

This layer is what the program uses in combination of the DEM to find an escape path out of the next layer, the hazard zone. This third layer represents the area where the population is at risk and must escape from. The fourth and final layer of this step is the safe zone which represents the area, where the population in the hazard zone can escape to. It should be noticed that although the study area can be a specific community, possible escape routes/safe zones must be considered from adjacent communities. Therefore, the same preparation should be done for all the adjacent communities, not just the study area. The safe zone can extend inside the at-risk area if there are any natural high areas and/or official vertical evacuation structures, where the population can be safe from the hazard. The final part of this step is the verification of the safe zone where the user analyzes the map to make sure that an area has not been erroneously added as a safe zone, which can happen due to issues such as projection errors.

Table 2-2 Default speed-conservation values and their corresponding land-cover types based on Soule and Goldman (1972) in the pedestrian evacuation analyst

	Land Cover Type		
Terrain Coefficient‡	SCV†	(Wood & Schmidtlein, 2012)	(Soule & Goldman, 1972)
2.1	0	Water, buildings, etc.	Loose sand
1.8	0.5556	Unconsolidated beach (sand)	Swampy bog
1.5	0.6667	Heavy brush	Heavy brush
1.2	0.8333	Light brush	Light brush
1.1	0.9091	Developed	Dirt road
1	1	Roads	Blacktop surface

The SCV values represent the inverse of the terrain coefficient except for loose sand that defaults to 0 in the PEA tool, assuming pedestrians cannot go through buildings or bodies of water in the event of an evacuation. Source: ‡ = (Soule & Goldman, 1972)*, † = Wood & Schmidtlein (2012)*

Step 2, the user will create the evacuation surfaces (path-distance raster) and maps using as input the previous mentioned preprocessed steps (DEM, least cost-inverse raster (SCV), and validated safe zone) to determine travel distance from every point in the hazard zone to the nearest point in the safe zone. Once this step is completed, the target-path distance raster is ready to be multiplied by the travel speed in the next step to determine the travel times to safety. The user will then screen out the result for any abnormalities, such as a very high change in travel time that can happen due to the quality/resolution of the DEM raster. If an unusual travel time is encountered, the user can set a default number as the largest possible travel time. This final procedure generates a time map (in minutes) from the evacuation-time surface by reclassifying the surface into an integer raster at 1-minute increment bands. This raster is then converted to polygons for use in the population analysis (Jones et al., 2014).

In *Step 3*, the user can use the time map generated previously to identify areas where the population will not be able to reach the safe zone in time. The user can now model potential VES in these zones to have an estimation of the number of people that could be saved. This new VES layer can be merged with the previous safe zone layer.

Step 4 is to input the population data layer in the PEA. The PEA tool uses this layer and the processed time map to determine the quantity and types of populations to reach safety before the set tsunami arrival time. The two default types of population, residents and employees, include public venues, community services, dependent-care facilities, and any other type of facility specified by the user. The PEA is designed to count population only within the hazard zone and the minimum expected travel time to safety is defaulted to 1 minute. Any fractional time is rounded up to the next minute (Jones et al. 2014)

Step 5 is the final step where the PEA tool will generate charts and maps that summarize the data in graphic format. These results allow the user to more easily understand and visualize the PEM results.

2.1.2. R.walk Anisotropic Cumulative Cost

Modeling human speed for purposes of walking and running have been well researched and documented in the past couple of decades. When it comes to modeling evacuation scenarios, two of the models most commonly used are Tobler's Hiking Function, and Naismith's Rule. Although different, both rules do a very good job at predicting evacuation time within a margin of error. The method used in this research is based on Naismith's rule found in the r.walk algorithm (Fontanari et al., 2015) of the QGIS software (QGIS Development Team, 2017).

Naismith's Rule, developed by Scottish mountaineer William Naismith in 1892, states that a person can walk 5 kilometers per hour on flat ground. An additional hour should be added for every 600 meters of ascend. Robert Aitken (1977) modified the Naismith's rule by changing the walking speed on flat ground to 4 km/hr. Eric Langmuir (1984) last modified Naismith's rule by saying that downhill travel costs less than flat ground travel, and therefore subtracted 10 minutes for downhill slopes between -5 and 12 degrees. Since steep downhill slope will negatively affect travel time, 10 additional minutes are added for negative slopes greater than 12 degrees.

Fontanari et al. (2015) expressed the Naismith/Aitken/Langmuir 's rule in the r.walk algorithm as:

$$\begin{aligned} \boldsymbol{T} = {} & [(\boldsymbol{a})\times(\boldsymbol{Delta\ S})] + [(\boldsymbol{b})\times(\boldsymbol{Delta\ H\ Uphill})] \\ & + [(\boldsymbol{c})\times(\boldsymbol{Delta\ H\ Moderate\ Downhill})] \\ & + [(\boldsymbol{d})\times(\boldsymbol{Delta\ H\ Steep\ Downhill})], \end{aligned} \tag{2-2}$$

where: T = time, a = time in seconds it takes to walk for 1 meter a flat surface (1/walking speed), b = additional walking time in seconds per meter of elevation gain on uphill slopes, c = additional walking time in seconds per meter of elevation loss on moderate downhill slopes (use positive value for decreasing cost), d = additional walking time in seconds per meter of elevation loss on steep downhill slopes (use negative value for increasing cost). Based on walking efforts in standard conditions, Langmuir proposed these default parameters for the r.walk algorithm: $a = 0.72$, $b = 6.0$, $c = 1.9998$, and $d = -1.9998$ (Fontanari et al., 2015).

The r.walk tool requires 3 main layers: DEM, friction cost (LULC), and start/end points layer. The tool also allows to input various parameters such as pace, type of least cost path neighborhood, maximum cumulative cost, maximum memory allocation, and more. The DEM provides the algorithm with the slope values. This layer is obtained from USGS (Taylor et al., 2015). The resolution of this layer consists of approximately 10×10 meters cells (1/3 arc).

The LULC is a raster layer in which each cell represents the terrain travel cost. For instance, paved roads provide the fastest travel time and, therefore, have a cost of 1.0 (travel time is not affected). Traveling on grass will affect travel time slightly and, therefore, have a cost of 1.1 (travel time slightly rises). A detailed list of the costs based on type of terrains is presented in Table 4-9.

The start/end points are the cells the r.walk tool uses to calculate travel time to all non-null cells using the least cost path algorithm.

A dimensionless scaling factor, lambda, is provided to control the effect of the friction costs. If given the value of 0, the LULC will have zero effect on the travel cost, if given the value of 1, the LULC will have full effect on the travel cost. By default, the LULC is fully considered.

The algorithm provides two neighborhood options to calculate the cumulative cost to determine the least cost path. Figure 2-2 shows the different neighborhoods proposed by the r.walk

```
x x x
x O x
x x x
```

(a)

```
  K   K
K x x x K
  x O x
K x x x K
  K   K
```

(b)

Figure 2-2 Friction cost estimation using: (a) normal neighborhood and (b) extended neighborhood (knight's move).

QGIS tool. Figure 2-2 (a) represents the cells that the algorithm always considers when calculating cumulative costs. Figure 2-2(b), represents the "knight's move", where additional cells (marked with k) are also taken into account to calculate the cumulative cost.

Using knight's move take additional time to process, but provides more precise results with the extended neighborhood. To achieve the best results, this PEM uses the knight's move. It is important to note that r.walk is based on r.cost by Awaida and Westervelt (2015). Graphical representation of the least cost evacuation paths are provided by r.drain by Miller (2001). An example using numerical values is presented in Figure 2-3.

Figure 2-3(a) shows the input map where the boxed cell with cost 3 is used as starting location. The output maps show the total cost of moving from each cell to the starting location. Figure 2-3(b) show the output map using the knight's move, whereas Figure 2-3(c) show the output map not using the knight’s move. The cells surrounded by asterisks are the different outputs from using the two neighborhoods.

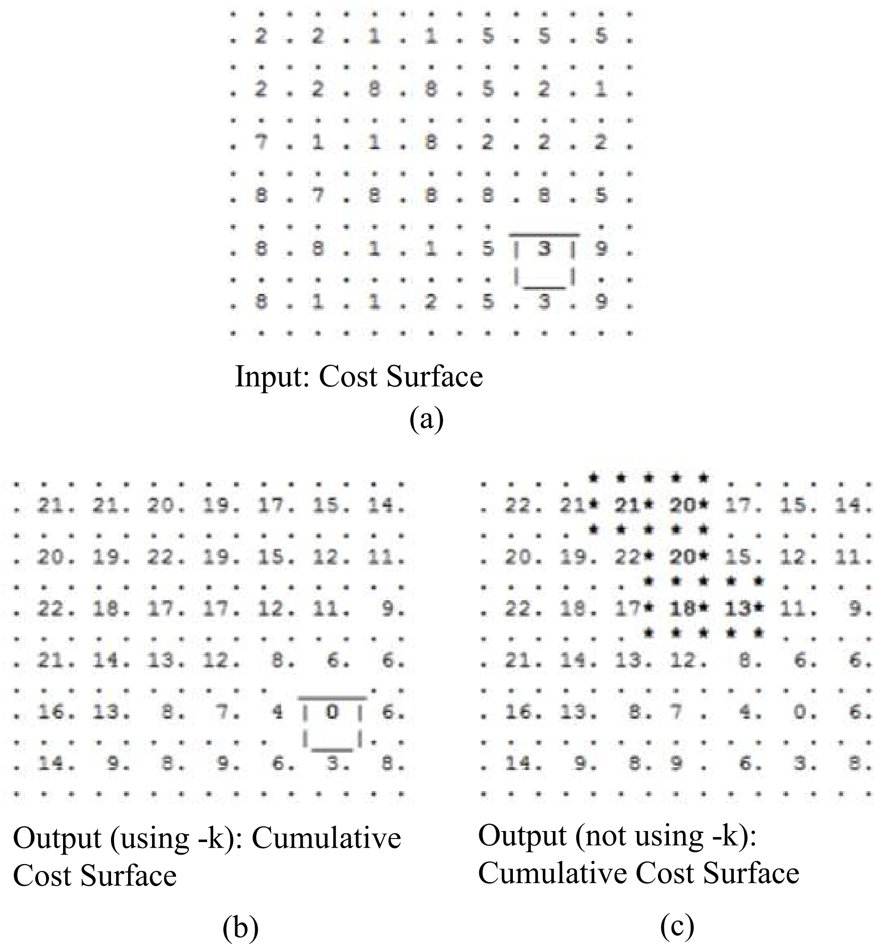


Figure 2-3 Example of (a) input cost surface and its output cumulative cost surface using (b) normal neighborhood and (c) extended neighborhood.

2.2 Group Pace Estimation

Although most of the population demographics is obtained from Census, the complexity of creating a realistic evacuation scenario called for higher level detailed than available from Census. As part of collaborative work to create this PEM, Hernández et al. (2017) used data from a five-kilometer (5k) race for the years 2013-2016. The race, called “El Corazón de la Montaña”, is held annually in Las Marías, PR (allsportscentral.com, 2017). Several reasons pushed the authors to select this race: proximity to Rincón, cross-country event is more representative of the evacuation terrain, and open participation to all people. Although the participants in this events are believed to be in above average physical condition, it was chosen as the closest representation of the Puerto Rican population that could be found at the time.

Although the data included the runners' gender, age, time to completion, and distance; only age and gender were considered. These two variables were used to fuse the 5k data with the population attributes available in the Census and ACS tables and, later, with the custom survey. Speed was calculated using the following equations:

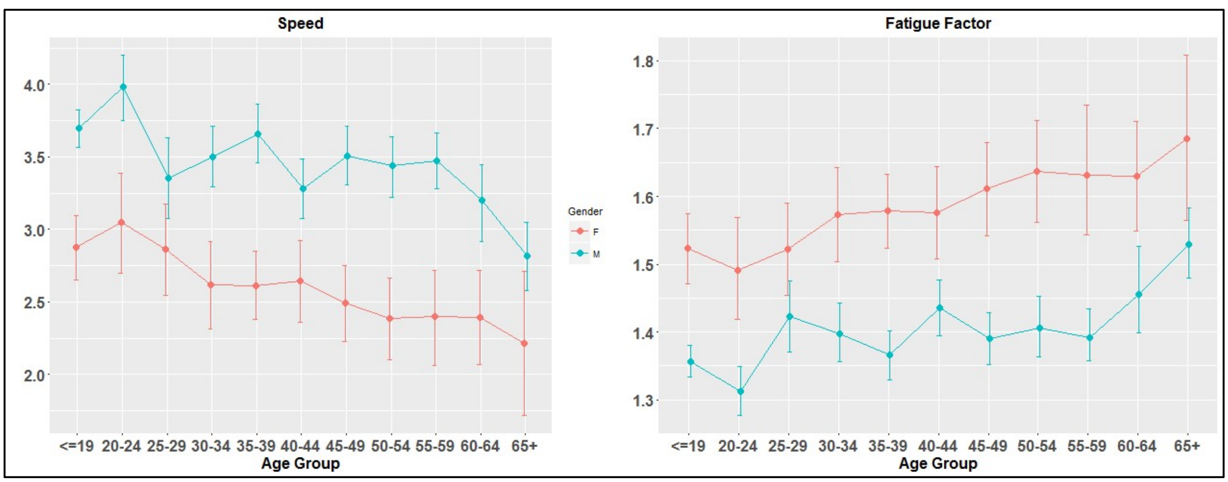
$$Speed = \frac{Distance}{Time}, \tag{2-3}$$

where: $distance = $ 5km, and $time = $ runner's completion time, $b = $ fatigue factor, $X = $ distance (km), $a = $ relative speed, and $t = $ time (min)

To unify the 5k data with other data sources used in the development of the proposed PEM, age groups were created to match those available from the Census, which range from under 19 to over 65 years old. Preliminary inspection of the data yielded 22 different combinations of age and gender (11 for male and 11 for female). Since the author's objectives was to reduce the number of parameters needed as inputs in the PEM, 22 different running speeds was deemed excessive and further analysis was carried out to reduce the total number of groups based on age and gender.

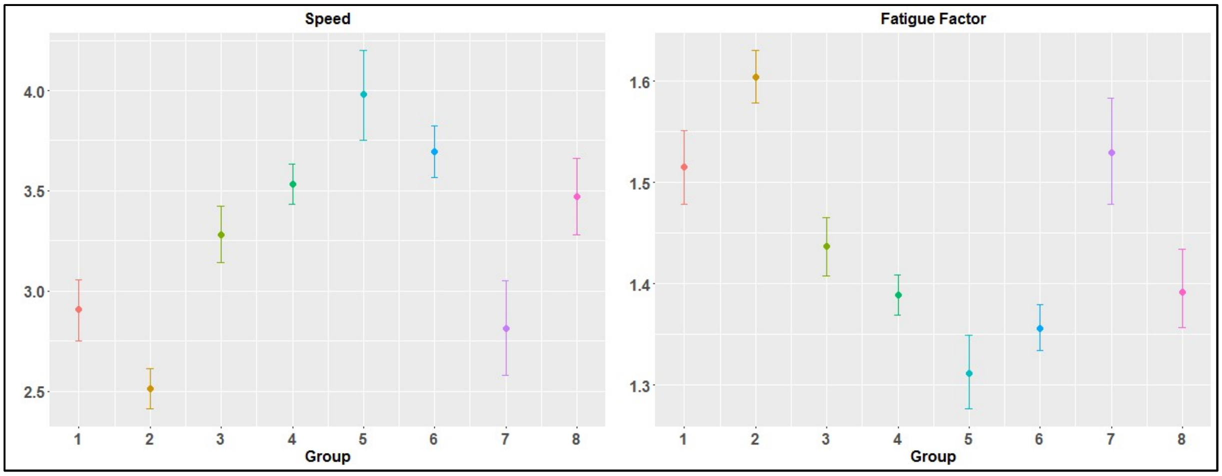
Hernández et al. (2017) used hypothesis tests on the medians and variances of the 22 combinations of age group and gender. The goal was to merge all those age and gender groups for which there was not a statistically significant difference in the medians and variances of the groups being merged. The null hypotheses stated that all groups being merged shared the same median and variance, respectively. When both null hypotheses could not be rejected, the authors would aggregate all data and form a single group. When at least one null hypothesis was rejected, another combination of age and group was being tested until no more groups could be merged.

Confidence intervals were used to preliminary inspect which groups could be assessed for merging. For all data, the assumption of normality was assessed, and whenever it appeared plausible, intervals based on a normal distribution were used. In those cases where the assumption of normality was not reasonable, bootstrap confidence intervals were used. Please refer to for a graph of the confidence intervals of the 22 categories for evacuation speed and fatigue factor. The confidence intervals of the group aggregation results are presented in Figure 2-5, where 8 distinct groups were obtained after going through the hypothesis tests and verifying there were not statistically significant differences in the medians and variances of the groups merged. Please refer to Table 2-3 for a detailed look on each group and their fitted distribution.



(a) (b)

Figure 2-4 Initial Graphed Confidence Intervals for the (a) Speed and (b) Fatigue Factor Data for All 22 Categories. Source: (Hernández et al., 2017).



(a) (b)

Figure 2-5 Confidence Intervals for the Proposed Aggregated Groups for: (a) Speed and (b) Fatigue Factor. Source: (Hernández et al., 2017).

Once the number of groups could no longer be reduced, the authors fitted to a probability density function for each of the new groups. These distributions, in turn were used to sample quantiles that were used in the sensitivity analysis for the proposed PEM. As in Jones et al. (2014b), the 15th, 50th, and 85th percentiles were used in the proposed PEM to depict slow, most likely, and fast run evacuation scenarios, respectively. A random speed scenario is also generated from the fitted distribution of each group to depict a more realistic scenario, where individuals within a group can have different evacuation speeds. Please refer to Table 2-4 for the different evacuation speeds considered for each group. Also, since no walking data was available for the population of interest, the walking speeds cited in the literature and described in Table 2-1 were used. Further note the same analysis described here was carried out for fatigue factor and its results are described in Table 2-4.

Table 2-3 Summary of results for speed data. Each row represents one of the proposed groups and KS and AD refer to the p-values for the Kolmogorov-Smirnov and Anderson-Darling goodness of fit tests, respectively. Source: (Hernández et al., 2017)

Group	n	Female Age Groups Present	Male Age Groups Present	Kruskal Wallis P-Value	Fligner Killeen P-Value	Distribution and Parameters	P-Value
1	98	≤19, 20-24, 25-29	-	0.772	0.199	Gamma (min=0, α=12.83, β=0.23)	KS 0.628 AD 0.485
2	168	30-34, 35-39, 40-44, 45-49, 50-54, 55-59, 60-64, 65+	-	0.734	0.960	Johnson SB (min=0, λ=8.01, γ=2.09, δ=2.58)	KS 0.693 AD 0.718
3	129	-	25-29 ,40-44, 60-64	0.973	0.343	Weibull (min=0, α=4.61, β=3.59)	KS 0.956 AD 0.974
4	238	-	30-34, 35-39, 45-49, 50-54	0.618	0.253	Weibull (min=0, α=5.13, β=3.84)	KS 0.783 AD 0.886
5	71	-	20-24	-	-	Weibull (min=0, α=4.72, β=4.10)	KS 0.677 AD 0.707
6	109	-	≤19	-	-	Weibull (min=0, α=6.52, β=3.97)	KS 0.961 AD 0.991
7	30	-	65+	-	-	Weibull (min=0, α=5.26, β=3.06)	KS 0.642 AD 0.667
8	37	-	55-59	-	-	Weibull (min=0, p=10.72, β=3.47)	KS0.867 AD 0.601

Table 2-4 Estimated percentiles for multiple case scenarios in the PEM. In terms of evacuation speed, the percentiles shown portray the following scenarios: slow (p15), average (p50), and fast run (p85). Source: (Hernández et al., 2017)

	Speed (m/s)								**Fatigue Factor**							
	1	2	3	4	5	6	7	8	1	2	3	4	5	6	7	8
p15	2.09	1.80	2.42	2.70	2.79	3.00	2.17	2.91	1.32	1.42	1.28	1.24	1.14	1.24	1.38	1.29
p50	2.84	2.47	3.31	3.58	3.79	3.75	2.85	3.52	1.51	1.58	1.41	1.36	1.29	1.33	1.50	1.37
p85	3.75	3.23	4.12	4.35	4.69	4.38	3.46	4.02	1.71	1.79	1.59	1.54	1.48	1.47	1.68	1.49

2.3 Evacuation Responses

PEMs try to simulate the behavior of a population during an emergency evacuation. The human being makes complex decisions, and during an emergency, sometimes these decisions stop being logical as fear and stress can impair the decision making process. It is very hard to replicate each decision as each is unique and subject to change at any time during the evacuation. However, although many PEMs do not consider a reaction time, some PEMs agree that there is a delay factor as to when someone starts the evacuation process. This delay factor can be caused by ignorance of what is happening, disbelief, waiting for an official notice, panic, or many more possibilities.

As part of the investigative group that contributed to the creation of this PEM, the assumption of people immediately evacuating at the onset of the hazard was relaxed using data from a stated response survey (Dávila et al., 2017). The survey was carried out on a sample of 192 residents and tourists from the municipality of Rincón, PR. All participants answered an open-ended question describing what they would do if they recognized one or more tsunami warning signals. These responses correspond to what the population stated would do if they recognized one or more tsunami warning signals. The remaining questions in the survey were either used as inputs for the PEM or for a flood vulnerability index for the municipality of Rincón, PR. For additional information on the stated response survey, please refer to Appendix I.

The stated responses in the survey were used to build a prediction model for the response of individuals based on the predictor variables and response described in Table 2-5. Dávila et al. (2017) considered a variety of classifiers such as random forests, decision trees, and linear discriminant analysis as potential prediction models. Since most of the respondents (56%) stated their evacuation response would be to *Evacuate Immediately*, an extensive parameter tuning was carried on the supervised learner' prior probabilities to be able to predict all other low frequency responses. A total of 16,275 combinations of parameters were tested, and the best set of prior probabilities was selected as the combination that minimized the five-fold cross validation error in each of the models (Dávila et al., 2017).

Table 2-5 Description of survey data and its role in the tsunami evacuation response prediction model. Percentages refer to how much of the sample corresponds to each of the observed categories. The term *first* when used in these responses refers to an individual evacuating after having accomplished the task described in the response.

Name	Type	Values	Role
Gender	Categorical	M (45%), F (55%)	Predictor
Age	Categorical	21-25 (11%), 26-30 (10%), 31-35 (11%), 36-40 (15%), 41-45 (10%), 46-50 (7%), 51-55 (11%), 56-60 (10%), 61-64 (7%), 65+ (8%)	Predictor
Resident status	Categorical	Resident (49%), Tourist (51%)	Predictor
Number in household	Categorical	1 (15%), 2 (24%), 3 (21%), 4+ (40%)	Predictor
Near dependent population	Categorical	0 (56%),1 (44%)	Predictor
Stated response: recognized tsunami warning signal(s)	Categorical	*Evacuate Immediately* (64%), *Gather Dependents First* (16%), *Contact Relatives First* (4%), *Help Others First* (5%), *Panic and Seek Help* (1%), *Panic First* (1%), *Seek Evacuation Assistance* (1%), *Wait for Official Notification* (1%), *Do Nothing* (7%)	Response

Table 2-5 shows the five-fold cross validation results of each of the classifiers. Three different performance measures were considered. Since no single classifier was the top performer across all measures, a desirability function weighting equally all measures was used to select a classifier. As the desirability function shows, the most suitable prediction model after scaling and pre-processing all performance measures was a random forest with a 20% cross-validation error rate, a 0.55 Kappa coefficient, and a 0.50 log loss. This model was used to predict an individual's probability of assuming each one of the following responses: *Contact Relatives First, Do Not Evacuate, Evacuate Immediately, Gather Dependents First, Help Others First, And Others.*

Table 2-6 Five-fold cross validation results for all supervised learners including three meta learners. The standard error (se) for all cross-validation folds in shown in parenthesis. Results shown consider linear discriminant analysis (LDA), decision trees (DT), random forests (RF), meta learner using learner discriminant analysis (ML-LDA), meta learners using decision trees (DT), and meta learner using random forest (ML-RF).

Learner	***Mean Error (SE Error)***	***Mean Kappa (SE Kappa)***	***Mean Log-Loss (SE Log-Loss)***	***Desirability***
LDA	0.36 (0.09)	0.23 (0.12)	18.83 (0.50)	68%
DT	0.33 (0.08)	0.31 (0.10)	23.84 (4.11)	71%
RF	0.20 (0.07)	0.55 (0.11)	0.50 (0.07)	100%
ML-LDA	0.25 (0.02)	0.66 (0.05)	83.39 (7.70)	67%
ML-DT	0.30 (0.04)	0.54 (0.11)	27.39 (5.07)	83%
ML-RF	0.24 (0.05)	0.6 (0.03)	33.10 (2.57)	86%

2.4 Reaction Time

Many will agree that after perceiving a threat's warning signals (e.g. ground shaking), people will delay their evacuation for a variety of reasons. Some of these reasons can be waiting for an official notification, gathering their dependents, contacting relatives, helping others, seeking assistance, getting important documents, and other possibilities. Depending on the circumstances, each person will experiment their own delay. It is, therefore, a hard and uncertain task to model accurate reaction times. Fraser et al. (2013) divide reaction time into two main behavioral components: *recognition* and *response*. Recognition is the time between taking knowledge of the danger, and the time at which a reaction is started. Response is the time between taking the first evacuation steps and the time when person starts moving towards a safe area. It is important to understand the complexity of these two behavioral components and quantify these delays to have an accurate and realistic evacuation time.

Post et al. (2009) defines total evacuation time in the case of local source tsunami as a function of the time for individuals to recognize a threat and decide to evacuate (IDt), the time it takes them to prepare to evacuate (EPt), and their travel time (TTt) so that:

$$ETt = IDt + EPt + TTt. \tag{2-4}$$

Supporting literature breaks down IDt and EPt even further by including institutional decision time (e.g. weather service assessment of the danger) and institutional notification time (e.g. local authorities message dissemination) (Yuzal et al., 2015). With such uncertainty and complex behaviors, it is inevitable not make some assumptions on a person or household unit reaction time. As mentioned in Fraser et al. (2013), "the use of stated intentions to estimate approximate evacuation departure times can provide some insight in the absence of observations of actual evacuation behavior in real events, but there is the potential to underestimate departure if we rely on this alone." Some PEMs set a fixed reaction to all agents (Yuzal et al., 2015), some only considers the institutional decision and notification time (Post et al., 2009), while others based the reaction time on a Rayleigh distribution (Mas et al., 2012; Imamura et al., 2011).

Proulx and Fahy (1997) presented five case studies showcasing the time delay to start building evacuation in case of fire. The warning signals are different than those for a tsunami evacuation, and building evacuation during a fire alarm does not have to deal with ground shaking. Nonetheless, the delay to start evacuating in terms of gathering personal stuff and so forth seem valid to consider a similar application in this PEM.

The case studies were conducted in the years 1993-1995 on midrise and high-rise apartment buildings. The average occupants are 150 for the midrise buildings, and 300 for the high-rise buildings. The reaction time for the 5 case studies are presented in 2-6. In Section 4.4.2 of the methodology, the reaction times presented in the drill section of 2-6 are used in conjunction with the Rayleigh distribution to estimate reaction times for the PEM.

Table 2-6 Average reaction time (in min:s) in the five case studies in the work by Proulx and Fahy (1997).

	DRILLS			FIRES		
	Residential Midrise	**Residential Highrise**	**Office Midrise**	**Forest Laneway Fire**	**World Trade Center 1**	**World Trade Center 2**
Good alarm	2:49	2:48 5:19 Winter	0:36 1:03 Cool			
Poor alarm	8:35			198:00	11:02	25:24

2.5 Fatigue Model

Emergency pedestrian models consider many factors such as type of terrain, terrain slopes, natural barriers, infrastructures, travel speed, and so on. It is common knowledge that after a combination of distance, travel speed, and/or terrain type, one will start to feel the effect of fatigue and therefore experience a slower pace. Unfortunately, the fatigue factor is usually ignored in most PEMs. In order to achieve a realistic pedestrian evacuation model, it is necessary to take into account the possible fatigue that people might experience during an evacuation.

Riegel, (1981) tackled this subject in his work "Athletic Records and Human Endurance." The author, interested in developing a pace prediction model based on time and distance, noticed that a log-log plot of time vs. distance approximates a straight line. Furthermore, the author discovered that the straight line created by the log-log plot of time vs distance for swimmers, roughly parallels that of runners, and other sports such as cross-country skiing, roller and speed skating, cycling, and more for time ranges from 3.5 to 230 minutes. Figure 2-6 shows the close parallel relation between a sample of the log-log plots for different sports.

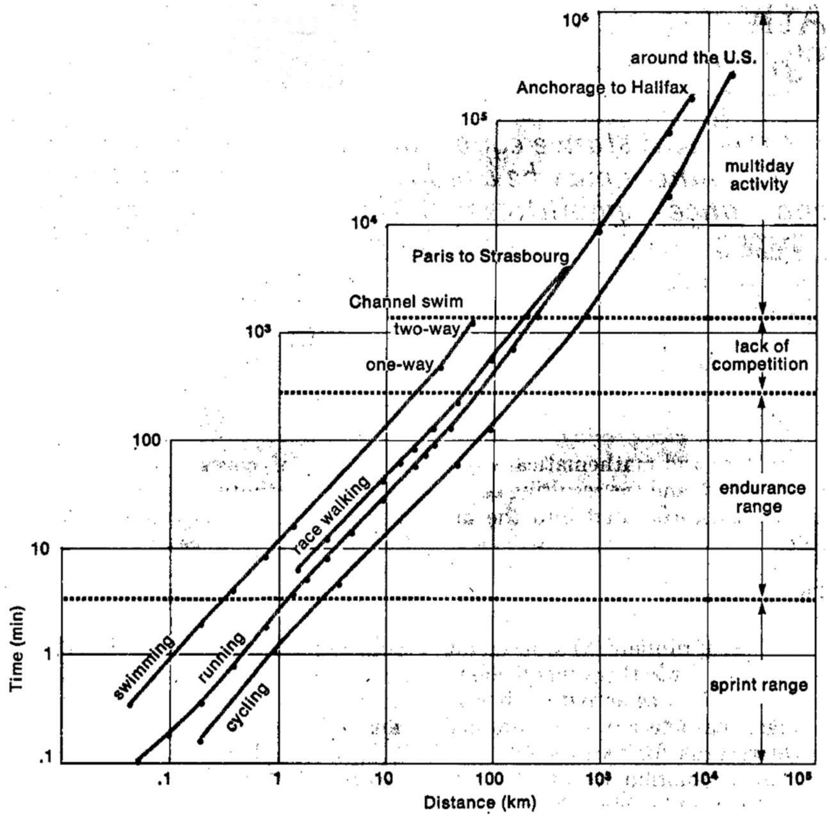


Figure 2-6 Human racing activity covers a large span of distance and time. World records are shown here for a swimming, race walking, running, and cycling. In the endurance range each activity appears as a straight line, which represents time as a simple power function of distance (Riegel, 1981).

It is important to note that linearity is lost for times below 3 to 4 minutes and above 230 minutes. To develop the endurance equation, ordinary least squares was used to estimate the endurance equation range to best fit the time vs distance plots to straight lines. The resulting equation only requires two constants to estimate time, speed, and distance:

$$t = ax^b, \tag{2-5}$$

$$b = \frac{\log(t) - \log(a)}{\log(X)} \tag{2-6}$$

where: t= time, x= distance, and a and b are constants that vary based on activity. Constant a is a measure of relative speed, and constant b is referred to by the author as the fatigue factor because it describes the rate at which constant speed decreases based on time and distance traveled (Riegel, 1981).

Table 2-7 Values for a and b for different sport events based on distance and time range. Source: (Riegel, 1981)

Activity	a*	b*	Distance range (km)	Time range (min)
Running, men	2.299	1.07732	1.5-42.2	3.5-129
Running, women	2.569	1.05352	1.5-42.3	3.9-131
Running, men over 50	2.841	1.05374	1.5-42.4	4.2-145
Running, men over 60	3.204	1.05603	1.5-42.5	4.9-168
Running, men over 70	3.654	1.0637	1.5-42.6	5.4-189
Running, men over 80	2.598	1.08283	1.5-42.7	3.9-147
Swimming, men	9.936	1.02977	0.4-1.5	3.9-15
Swimming, women	10.578	1.03256	0.4-1.5	4.1-16
Nordic skiing, men	2.836	1.01421	15-50	44-149
Race walking, men	3.565	1.05379	1.6-50	5.9-222
Roller skating, men	1.589	1.13709	3.0-10.0	5.6-22
Cycling, men	1.015	1.04834	4-100	4.4-128
Speed skating, men	1.266	1.06017	3.0-10.0	4.1-15
Man-powered flight	3.238	1.10189	1.8-36.2	6.4-169

*based on records of up to November 1st, 1979

Similar fatigue factors are observed between women and men in their respective activities. The author analyzes furthermore the relation between the data obtained from competitive sports and the data from non-competitive activities. The decrease in performance was observed to be relatively the same across all activities. For instance, if a non-professional runner performance matched 70% of the time it would take a world-class runner, the same 70% performance is also observed for other type of activities. The endurance equation is therefore applicable to predict time, distance, and speed for non-competitive sports as well.

Hernandez et al. (2017) used marathon data to estimate fatigue factor for the marathoners, as presented in Table 2-4. In this work, we adopt the approach by Hernández et al (2017) where the fatigue factor calculated for each group pace, as mentioned in Section 2.2, was used to penalize the travel time for distances over 1000 meters.

3 Contributions To The Literature

In the fight to mitigate natural events such as earthquakes and tsunamis, numerous efforts have been made. Pedestrian simulation models use many different approaches such as, anisotropic least cost path (Wood & Schmidtlein, 2011), multi-agents (Dijkstra & Timmermans, 2002), a hybrid approach that combines elements of the multi-agent systems approach with cellular automata (Tissera et al., 2007), and more. They all have contributed to the literature and provided different insights on tsunami evacuation. The models presented in this PEM are all parts of a microscopic approach to simulate evacuation scenarios. The complexity of human behavior in decision making makes it nearly impossible to capture every single human reaction into a single evacuation model. Therefore, combining different approaches that target different aspects in human behavior can reduce the complexity and minimize assumptions. Each approach handles different aspects of the simulation and help recreate a scenario very hard to implement in a laboratory setting. As noted by Wood and Schmidtlein, (2011), when comparing ALCD to ABM systems, the two approaches need not be exclusive of each other and ideally, a mixed-methods approach could be applied to fully appreciate the complex nature of pedestrian evacuation. In this work, an ALCD approach will be augmented with ABM approaches to simulate a potential tsunami evacuation for the municipality of Rincón, PR. The specific contributions of this work are described next.

3.1 Improved Population Distribution

Using U.S. Census, ACS, and PR Planning Board data, this PEM can accurately distribute the population at a sub-county level with respect to age, gender, employment status, and household size. This PEM introduces a family-unit-based evacuation that allows anything from individuals evacuating by themselves to individuals evacuating in groups of up to 9 people. Groups larger than one within a household structure are assumed to evacuate together. Relaxing the assumption of random population distribution by introducing family unit evacuation times will allow to better capture the reality of an emergency evacuation.

3.2 Evacuation Response

A survey was distributed to the local and tourist residents of Rincón to collect stated evacuation responses in case of a tsunami, among other collected information. Based on the collaborative work by (Dávila et al., 2017), groups based on age and gender were created and assigned evacuation responses.

3.3 Fatigue Factor

During a real evacuation, one cannot deny the fact that there is some degree of fear that can negatively affect the evacuation process. Everyone's response is unique and may vary according to multiple factors. Depending on the distance, speed of travel, and physical condition of each person, fatigue can have a considerable effect on evacuation time. It is therefore important to understand and group the population based on certain characteristics to calculate a fatigue factor, which in turn can help in the better estimation of the evacuation time. In the context of this work, a fatigue factor based on the work by Riegel (1981) is introduced as a penalty on the evacuation time.

3.4 Reaction Time

During an emergency evacuation, people seldom have the possibility to evacuate right away. Each person perceives the danger in their own way and will set priorities accordingly. Some people can be calmer and start evacuating peacefully, whereas others can start panicking and rushing toward the safe zone. To relax the assumption that all individuals evacuate immediately and at the same time, the stated evacuation responses in the survey were used to estimate a reaction time based on supporting literature on reaction time by Mas et al. (2012), Imamura et al. (2011) and Proulx and Fahy (1997).

3.5 Custom Geo-Referenced Inventory

Another challenge specific to Rincón is that there is no single repository of geo-referenced data of the residential, critical, essential, and public infrastructure. While Rincón is fairly dense for its size (1,063.8/sq mi) (U. S. Census Bureau, 2015), many of its essential and critical infrastructures, as well as population are concentrated around the coast line and inside the TEZ. This can create a problem during a tsunami evacuation because the emergency personnel themselves must also evacuate. The creation of this custom geo-referenced database of the municipality's infrastructure will allow the PEM to be based on an accurate depiction of the infrastructure inside and outside of the hazard zone and the natural boundaries (e.g. buildings) blocking the evacuation paths of individuals in the event of an evacuation.

4 CHAPTER – METHODOLOGY

This chapter presents a detailed description of the proposed PEM including the data sources and processes used as inputs. This approach targets certain aspects of human behaviors during an evacuation that many PEMs fail to target. When a natural disaster such as a tsunami happens, family units often evacuate as groups with a pace dictated by one of the individuals in the group. During this evacuation, the terrain type and slopes can play a significant role on the speed at which the population is traveling. The correct classification on the structures in the TEZ area is important to correctly map single family homes, apartment complexes, commercial, and public facilities. By taking these different aspects into consideration, this PEM can create a family-structure-based anisotropic evacuation, where travel is not limited to roads networks. The outputs of this PEM go through a post-processing process where reaction and fatigue times are added. Figure 4-1 provides an overview of the approaches used to create this PEM.

This PEM is based on three main inputs: population, LULC, and study area. Most PEMs randomly distribute the population in the at-risk area. This random distribution does not usually consider family structures and sub-county population distribution. The very first part of this PEM is to relax this assumption, and uses data from the US Census Bureau and ACS to create family household units representative of the sub-county population of the study area. The next step is to process the LULC layers based on a combination of data: land cover, road network, structures, and the DEM layer. The study area is then divided into the TEZ and the safe area. Cutting the different layers to the TEZ instead of the study area saves considerable time in data processing.

Based on empirical research, Tobler's function, presented in Tobler (1993), and the Naismith/Aitken/Langmuir's rule, presented in Fontanari et al. (2015), are the two most common methods to tackle anisotropic travel time. Although Tobler's function and Naismith's rule are similar, Langmuir modified the latter to penalize steep downhill slopes of greater than 12 degrees. This PEM is based on a combination of the Naismith's rule and ABM evacuation models. This function can be found in the r.walk travel cost algorithm found in the QGIS software. Once the PEM outputs the preliminary results, reaction time and fatigue penalties are added in the post-processing of the household unit evacuation times.

The remaining paragraphs of the methodology sections will present in detail these three categories as well as their inputs. Please refer to Figure 4-1 for the conceptual map of this PEM's methodology.

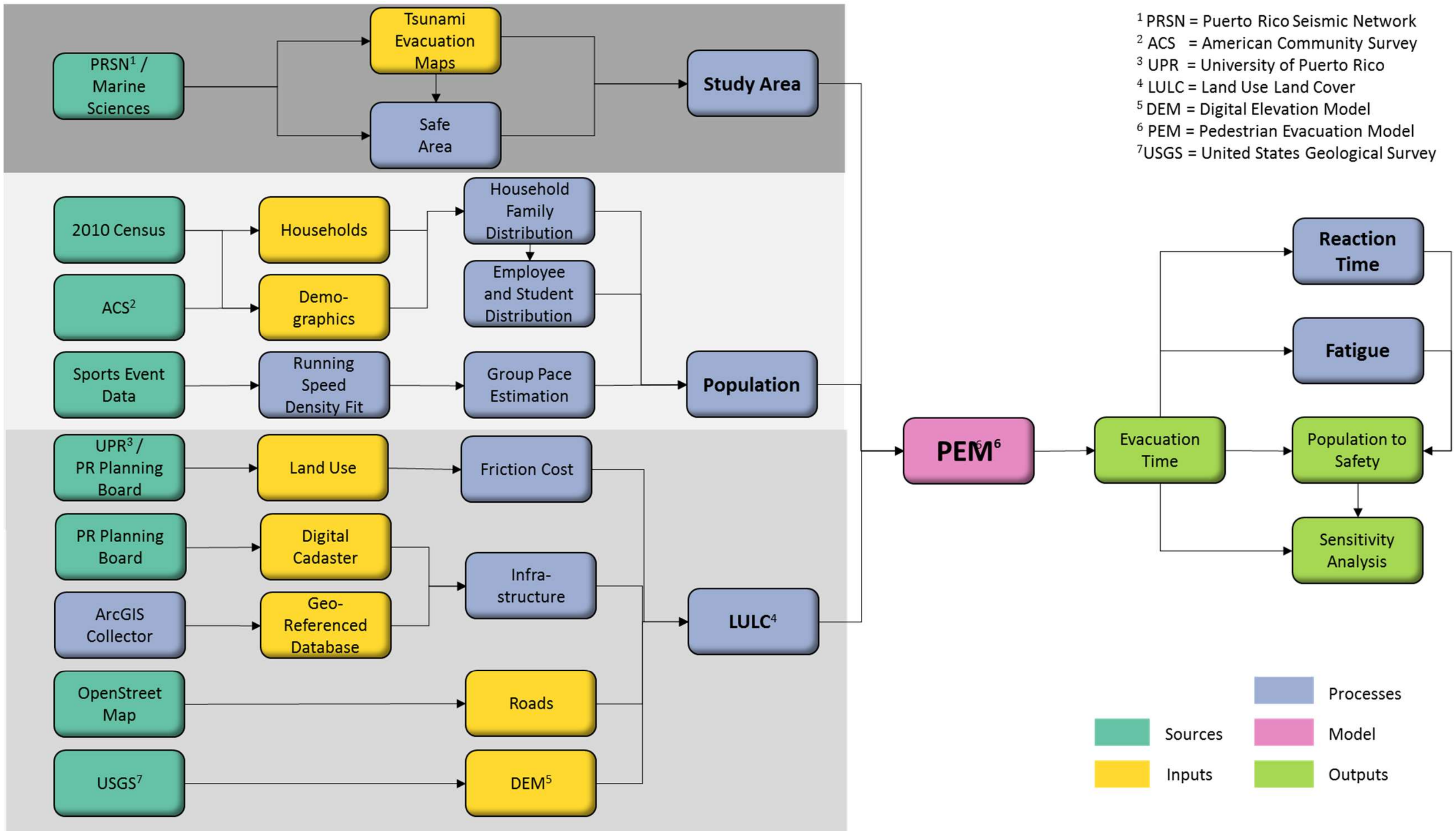


Figure 4-1 Conceptual map of the proposed pedestrian evacuation model (PEM).

4.1 Study Area

On October 11th, 1918, Puerto Rico witnessed a strong earthquake of magnitude 7.3 affecting the western and northwestern parts of the island. Many cities were affected and the total death toll was estimated to be 116 people and the economic toll was calculated to be 4 million dollars, twice the island's budget at the time (Pacheco & Sykes, 1992; Puerto Rico Earthquake of 1918, 2005). Rincón, one of the closest city to the earthquake epicenter was not as structurally affected as the other cities such as Aguadilla, but the subsequent tsunami waves reached Rincón's coasts first. Recently, Rincón has bloomed in one of the most attractive touristic destination of the island. Tourists, mostly surfers, arrive throughout the year. When added to the local tourist population, this town of roughly 15,000 people can see its population grow 8 times bigger and reach up to 120,000 people during special celebrations such as the Rincón Film Festival or the Corona Pro Surf Circuit. Considering the historical tsunami and the potential damages to human lives and the local economy, Rincón was chosen as the study area for this PEM.

The study area, shown in

Figure 4-2, includes Rincón as well as two adjacent communities: Aguada (Río Grande sub-county) and Añasco (Caguabo sub-county). The rationale behind this is the fact that the TEZ areas of the three municipalities intersect. It is, therefore, important to map the safe area outside of the joined TEZ and realize that during evacuation people will not restrict themselves to municipality limits, but will reach whatever safe area is closest. It must be noted, nonetheless, that the PEM only targets the people inside Rincón TEZ to simulate their evacuation toward the safe area.

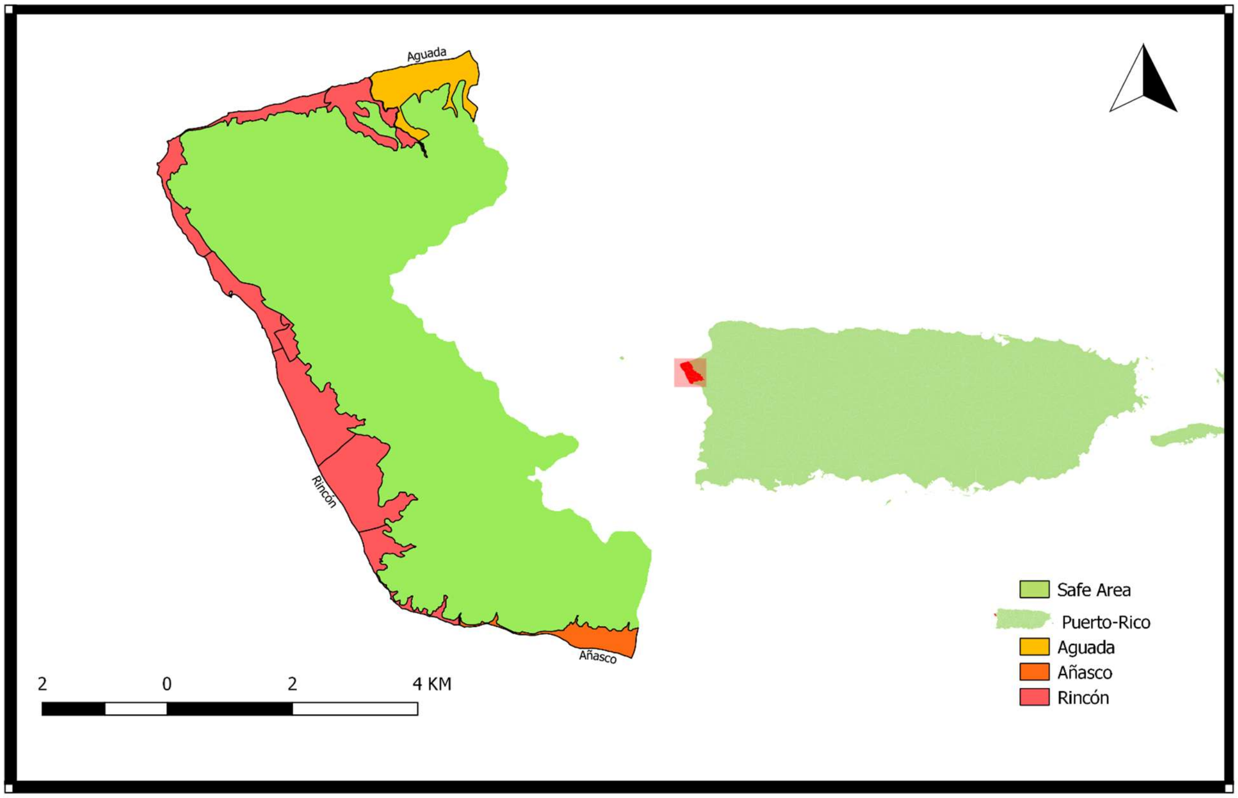


Figure 4-2 Map of the study area which includes Rincón, PR and two sectors (Río Grande and Caguabo) of two neighbor municipalities (Aguada and Añasco).

4.1.1. Tsunami Evacuation Maps

The TEZ is used to identify the areas subject to floods as a result of a tsunami and the TEZ shapefiles for Rincón, Aguada, and Añasco were obtained from the collaborative work between the Puerto Rico Seismic Network (PRSN) and the Department of Marine Sciences at UPRM. (PRSN, 2015). Although the actual TEZ area might be smaller, the inundation maps were expanded to natural borders such as roads, city limits, and so on. Using QGIS, a simple attribute feature selection was used to select and join the TEZ of Rincón, Aguada (Río Grande), and Añasco (Caguabo). Once joined, they formed a new layer thereafter referred to as TEZ. Figure 4-3 shows the official TEZ area for the cities of Rincón, Añasco, and Aguada.

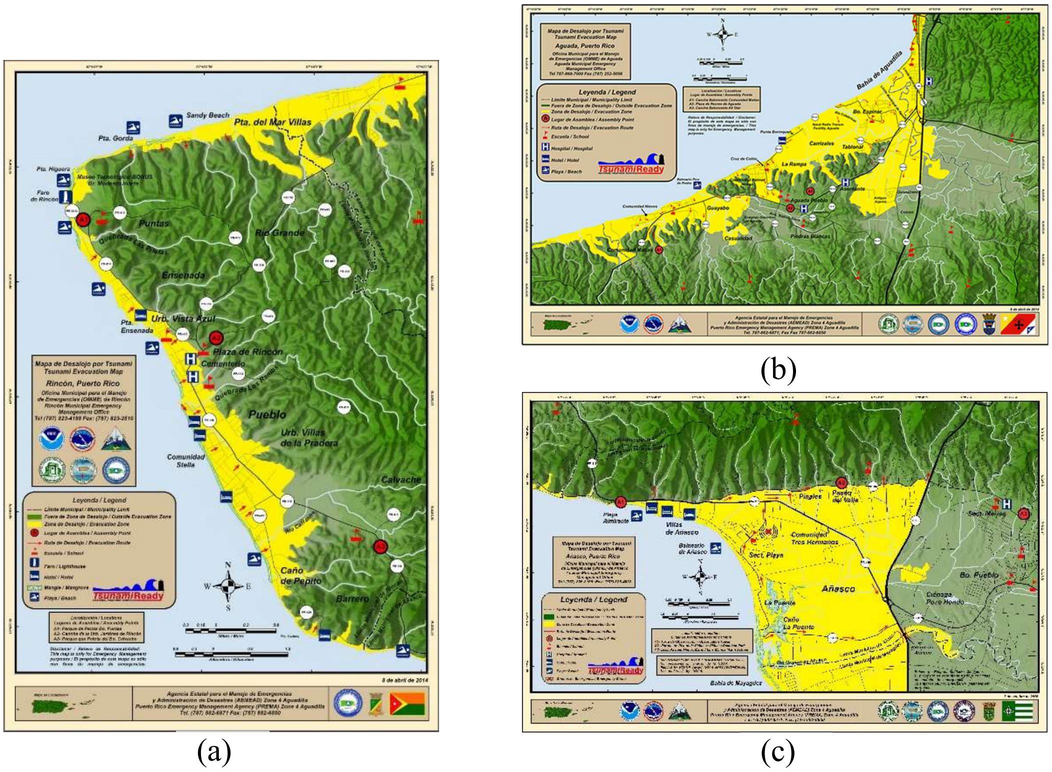


Figure 4-3: The different TEZ of the study area: (a) Rincón, (b) Aguada, and (c) Añasco. Source:(PRSN, 2015).

4.1.2. Safe Area

The safe area represents all the inland areas outside the TEZ. Therefore, once the TEZ layer is obtained, the safe area is calculated by using QGIS' difference tool, eliminating the TEZ from the study area. Similar to the TEZ, the adjacent communities of Aguada (Río Grande sub-county) and Añasco (Caguabo sub-county) are included to allow pedestrians evacuation to these areas. The safe area is inputted in the PEM as a raster layer with cell values equal to 0 to allow the r.walk algorithm to go from higher values to lower values cost cells until they reach cost 0 (safe area). Please refer to Figure 4-4 for a map representing the TEZ and the safe zone of the study area.

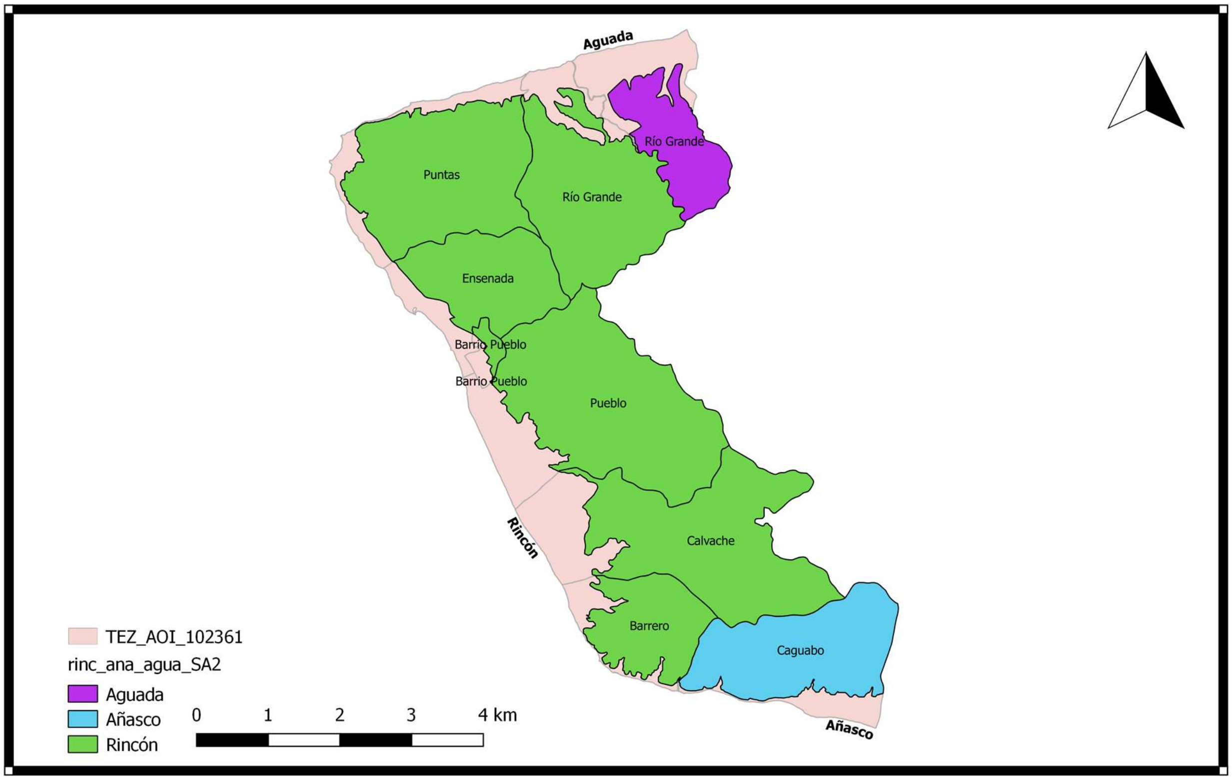


Figure 4-4 Tsunami evacuation zone (TEZ) and safe zone for the study area including all sub-counties in Rincón as well as the Río Grande and Caguabo sub-counties in Aguada and Añasco, respectively.

4.2 Population

Agent-based PEMs evaluate an emergency evacuation at a microscopic level. One of the main input of such a model are the agents and their geographical location in the event of a threat. As previously described in Figure 4-1, population is one of three main inputs to this PEM and this layer is divided into family household units. For the purposes of a model, every family within a single structure is treated as a single agent with a pace dictated by the slowest adult member in the group.

4.2.1 Household Family Distribution

To relax on the assumption of random placement of the population in the hazard zone, the data obtained from US Census and ACS was used to assign attributes such as age, gender, employment status, population count, and household count to each individual within the hazard zone. Then, using these characteristics and the custom geo-referenced inventory of infrastructure, an initial geographical location was assigned to each individual at the start of the proposed PEM.

A simulation model output depends heavily on the quality of its input data. The more precise the family distribution, the better the results depict the number of individuals that can reach safety in the event of an evacuation and their evacuation times. Although general population count is readily available from Census and ACS, the level of details needed to separate the general population into households' family units of 1, 2, 3, or 4+ members is not available. This section intends to combine different sources of information to configure families including their characteristics (e.g. age, gender) to form family household units that evacuate as a group. Please refer to Table 4-1 for the different tables, their sources, and how they are respectively used in the PEM.

Table 4-1 Census and ACS tables used in this PEM, their sources and how they were used.

Table	*Source*	*Uses*
B11016	American Community Survey (ACS)	Household type by household size. Used to estimate the number of houses per household size.
DP1	Census 2010	Rincón's population distribution by gender and age. Used to create population with unique ID.
Rincón Digital Cadaster	Puerto Rico Planning Board	Geographical coordinates for uniquely identified structures. Used to set the initial location of the population in the proposed PEM.
B23001	American Community Survey (ACS)	Used to estimate employment data on sub-county level
Appendix I	Custom Survey (Q1, Q2, Q5, Q6, Q10, Q25)	Questions related to attributes and stated response in the event of tsunami. Used to estimate the percentage of dependents per household size.

A custom data manipulation code, written in R, was used to create household family units of sizes 1 to 4+ members and link each family to a household. Refer to Table 4-2 and Table 4-3 for the US Census and ACS based population distribution for Rincón, PR, and to Table 4-4 for the aggregated population tables of 1 to 4+ persons' households.

Table 4-2 ACS Table B11016 showing the number of family households per barrio divided by number of persons per household

	Family households:					
	2 persons	**3 persons**	**4 persons**	**5 persons**	**6 persons**	**7+persons**
Atalaya	77	41	51	0	0	16
Barrero	100	35	26	13	0	13
Calvache	267	56	182	33	0	0
Cruces	196	108	41	21	0	12
Ensenada	148	126	37	9	27	0
Jagüey	67	35	55	53	0	0
Pueblo (Corcega)	344	252	394	75	0	0
Puntas	276	166	37	36	0	0
Rincón Pueblo	100	30	72	11	9	0
Río Grande	111	67	110	32	0	0

Table 4-3 ACS Table B11016 showing the number of non-family households per barrio divided by number of persons per household.

	Non-family households:						
	1-person	**2-person**	**3-person**	**4-person**	**5-person**	**6-person**	**7+-person**
Atalaya	102	10	0	0	0	0	0
Barrero	138	16	0	0	0	0	0
Calvache	222	22	0	0	0	0	0
Cruces	77	15	0	0	0	0	0
Ensenada	137	28	0	0	0	0	0
Jagüey	41	0	0	0	0	0	0
Pueblo	428	36	0	0	0	0	0
Puntas	258	14	0	0	0	0	0
Rincón Pueblo	105	0	0	0	0	0	0
Río Grande	109	28	0	0	0	0	0

Table 4-4 Aggregated ACS Table B11016 showing family and non-family households of 1, 2, 3, and 4 or more persons.

	Total Households			
	1-person	**2-person**	**3-person**	**4+-person**
Atalaya	102	87	41	67
Barrero	138	116	35	52
Calvache	222	289	56	215
Cruces	77	211	108	74
Ensenada	137	176	126	73
Jagüey	41	67	35	108
Pueblo	428	380	252	469
Puntas	258	290	166	73
Rincón barrio	105	100	30	92
Río Grande	109	139	67	142

The creation of the family household structure is divided into six sections: input files, household structures, total population, family households with dependents, family households without dependent, and validation of results. A linear program (LP) is used to estimate the number of houses of size 1, 2, 3, and 4 necessary to fit the number of people available for each sector, subject to the digital caster and population restrictions. The objective function of this LP is to maximize the population being distributed to households' sizes 1 to 4 where x_i represents household of size i, and the coefficient represents the number of people to be fitted in that household size.

$$Max\ x_1 + 2x_2 + 3x_3 + 4x_4 \qquad (4\text{-}1)$$

Subject to:

$x_i \leq UH_i \qquad \forall\ i = 1,2,3,4$

$x_i \geq LH_i \qquad \forall\ i$

$\sum_{i=1}^{4} x_i \leq H$

$x_1 + 2x_2 + 3x_3 + 4x_4 \leq P,$

where: x_i represents household of size i, UH_i and LH_i respectively represents the maximum and minimum number of households of size i, H represents total number of households, and P represents total number of people per sub-county.

Since Census tables do not break down the population in sub-level households' categories, various questions (e.g. Q2, Q10) of the custom survey in Appendix I were used to estimate the number of dependents per household sizes. The Rincón's residents respondents were asked the total number of people that lived in their households based on age categories (e.g. less than 18 years old, between 18 and 65 years old, and over 65 years old). They were also asked the number of dependents in their households based on the same age categories. The responses for these two questions were used to estimate the household size (i.e. number of individuals leaving in the same household) and also the number of dependents per household size.

Although based on US Census and ACS data, some assumptions had to be made in creating the family household units. The level of details available on the tables used only allowed specific age brackets (e.g. 0-4, 5-9, 10-14, …, 60-64, 65+ years old). Although the legal age of majority in Puerto-Rico is 18 years old, due to the fact that ages 18 and 19 are within the same age group in the Census DP1 table, all individuals 19 years old or younger were treated as dependents for the purposes of this PEM. Another assumption made in the PEM is that all household units with dependents have at least one adult (20 years old or older). To comply with this restriction, the model first creates and distributes the dependents population in the number of household units with dependents. For each household unit with dependent population, adults are added based on the household size. For instance, a household of size 2 may only receive 1 dependent and 1 adult, or just 2 adults.

Aside of household size 1 with just 1 adult, each of the household types have different number of dependents. Let $HH_{i,j}$ denote the number of households of size i with j dependents. Then, households of size 2 can only have 1 dependent ($HH_{2,1}$), but households of size 3 can have 1 or 2 dependents ($HH_{3,1}$, $HH_{3,2}$), and households of size 4 can have up to 3 dependents ($HH_{4,1}$, $HH_{4,2}$, $HH_{4,3}$).

For HH_2, the model will first place a female adult 20 to 40 years older than the oldest dependent. A male adult no more than 10 years younger or 10 years older than the female adult is then added.

In cases where no individuals that fit the age restrictions remain unassigned, any random adult will be added. The model execution order starts creating dependents households' family units with 1 adult and 1 dependent, giving priority to dependents, and then adults. The specific execution order is the following: $HH_{2,1}$, $HH_{3,2}$, $HH_{4,3}$, $HH_{1,0}$, $HH_{3,1}$, $HH_{4,2}$, $HH_{2,0}$, $HH_{4,1}$, $HH_{3,0}$, and $HH_{4,0}$.

Once the model creates the family household units with dependents, more often than not, some remaining dependent population are left. The model randomly distributes them to households of 2 or more adults with dependents. The same process is then repeated for the remaining adults. As a final step, if there are still remaining adults and houses, the code will randomly distribute the adults in households' sizes 2 and higher while updating the households size with the correct number of members. This final random distribution will create a variety of household sizes of up to 9 members.

At this point, all the agents created are distributed into single family households. The next step is to distribute agents into condominiums. This step is based on actual field work where a sample of the condominiums in Rincón were selected and their total number of apartments visually estimated. Each condominium structure is then filtered out and the appropriate number of apartments are created. In cases where agent groups were already assigned to the condos, they are redistributed to the condo population. Although the condominiums population is randomly created, some basic constraints are added: maximum of 5 agents per apartment, at least one agent 20 years or over is assigned to each apartment. Similarly to single family units, agents assigned to apartments evacuate together.

A random distribution creates a needed level of variability that sometimes does not conform to the margin of error found in the US Census and ACS tables. Ten iterations of the model are performed to obtain the combination of results with the lowest error and within the limits of the population and household size distribution. Once the best iteration is selected, each group is assigned to a structure from the digital cadaster that would represent the initial location of the group in the PEM. Table 4-5 and Table 4-6 show respectively the limits of households and number of dependents and adults as extracted from Census tables.

Table 4-5 Upper and lower limits of the household sizes per sub-county where $UL = upper\ limit$, $LL = lower\ limit$, and $HHi = household\ of\ size\ i$

	UL HH_1	UL HH_2	UL HH_3	UL HH_4	LL HH_1	LL HH_2	LL HH_3	LL HH_4
Atalaya	168	151	104	228	102	87	41	67
Barrero	218	204	90	202	138	116	35	52
Calvache	313	444	114	426	222	289	56	215
Cruces	131	312	190	223	77	211	108	74
Ensenada	208	277	209	220	137	176	126	73
Jagüey	80	122	103	282	41	67	35	108
Pueblo	564	538	373	739	428	380	252	469
Puntas	365	403	243	225	258	290	166	73
Barrio-Pueblo	168	165	74	243	105	100	30	92
Río Grande	172	227	136	311	109	139	67	142

Table 4-6 Number of dependents and adults per sub-county where $M = Male$, $F = Female$, and $Dep = Dependents$

Sector	M Dep	M Adults	F Dep	F Adults
Atalaya	125	344	134	353
Barrero	153	377	128	426
Calvache	273	825	246	878
Cruces	193	491	193	540
Ensenada	162	452	166	548
Jagüey	88	268	87	259
Pueblo	540	1302	496	1458
Puntas	152	610	171	642
Barrio-Pueblo	100	330	98	405
Río Grande	162	431	136	458

4.2.1.1 Employee Agent Creation

Using the household family distribution, employee distribution data, extracted from Census Table B23001, was used to create the employee distribution. Most businesses in Rincón are small businesses and in order to model the employee population, an assumption was made that the majority of the employees are actual Rincón residents. This model allows to select and change the status of residents' population that were home during the night time scenario, to employees that are now moved to designated commercial buildings. The employee distribution is based on age, gender, and sub-county. Using upper and lower count margins, the model loops through each sub-county to create the appropriate agent distribution based on age and gender. The designated commercial and hybrid buildings are then selected where agents are randomly placed. Where in the residential distribution, the number of agents in a household was used as household size, in the case of commercial structures, the total number of employees per building is used. In the household family distribution, family units were created to simulate evacuation as a group, the employee agent on the opposite are not set as groups in order to simulate personal evacuation.

4.2.1.2 Student Agent Creation

Similarly to the employee agent creation, student agents are created by extracting the 19 and under population from the household family distribution. Using student data obtained from Noodle, (2017) and Eladrel Technologies LLC, (2017), the student and teacher population in Rincón was estimated, and agents were created and placed in each public school. Since household size does not directly apply, the average size per classroom is used by calculating the ratio of number of students per teacher. Groups of students agents will evacuate with the teachers. Please refer to Table 4-7 for the student data per school.

Table 4-7 Student estimation for the different schools in Rincón.

Name	Total	F%	M%	From age	To age	Teachers
Manuel Garcia Perez	450	0.54	0.56	15	19	32
Octavio Cumpiano	154	0.43	0.57	4	14	8
Genoveva Perez	140	0.41	0.59	4	14	13
Jorge Seda Crespo	371	0.5	0.5	9	14	26
Conrado Rodriguez	283	0.43	0.57	0	9	24
Juan Ruiz Pedrosa	251	0.5	0.5	9	14	24

4.2.2 Group Pace Estimation

To properly model pedestrian evacuation, one must consider the different physical aptitudes of the population. The walking speed of individuals has been described in the literature to fluctuate between 0.8 m/s and 1.8 m/s, 1.1 m/s being the most commonly cited value in the literature (NZ Transport Agency, 2009; Wood & Schmidtlein, 2011). For the purposes of this work, the groups and their respective running speeds created in the work of Hernández et al. (2017) were used. For the walking speed scenarios, no data was available for the population of interest. Hence, the commonly used fast and slow walking speeds found in transportation research and in many PEMs were used instead. Overall, walking and running speeds, six different evacuation scenarios are evaluated in the sensitivity analysis: $slow$ and $fast$ walking speeds and $slow, median, fast,$ and $random$ running speeds. Please refer to Table 4-8 for the different evacuation speeds used in the proposed PEM.

Table 4-8 Time in seconds it takes to cross 1m on a flat surface for the different walking and running pace scenarios

	No group	1	2	3	4	5	6	7	8
Slow run	-	0.48	0.56	0.41	0.37	0.36	0.33	0.46	0.34
Median run	-	0.35	0.40	0.30	0.28	0.26	0.27	0.35	0.28
Fast run	-	0.27	0.31	0.24	0.23	0.21	0.23	0.29	0.25
Random run	-	0.57	0.31	0.31	0.24	0.29	0.22	0.31	0.33
Slow walk	0.83	-	-	-	-	-	-	-	-
Fast Walk	.66	-	-	-	-	-	-	-	-

To generate the raster layers with the cumulative travel costs, a batch process of the r.walk algorithm is used in QGIS. Each line of the batch process interface, as shown in Figure 4-5, represents one of the 8 categorical groups with their respective speeds. The batch process outputs a cumulative cost and movement direction layer for each group that can be used in conjunction with the households' family distribution to extract their corresponding travel time to safety.

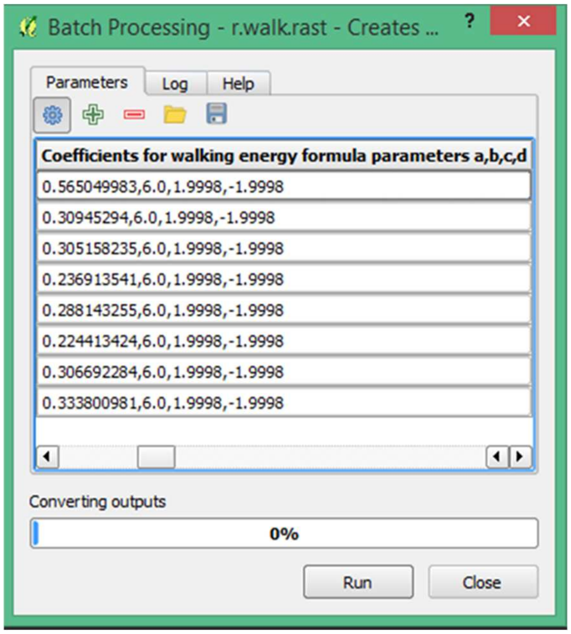


Figure 4-5 r.walk batch processing input showing the different coefficients for walking energy used for the 8 groups. Source:(Fontanari et al., 2015).

4.3 Land Use Land Cover (LULC)

Most pedestrian evacuation models consider the environment where the evacuation is taking place. In this PEM, the LULC section covers the type of terrain, the infrastructure, the roads, and the digital elevation model (DEM) as presented in Figure 4-1. The LULC layers have two main functions. One is to provide the escape route for the population being studied. The second is to introduce constraints to the possible escape routes. For instance, buildings, lakes, rivers, or high walls represent constraints that are extremely costly to cross by evacuees. The LULC layers are composed of four distinct layers: type of terrain obtained from the University of Puerto Rico at Río Piedras (UPR-RP) and the PR Planning Board, road layers obtained from OpenStreetMap, building layers obtained from PR Planning Board, and the digital elevation model (DEM) obtained from USGS.

Combining all these layers creates a detailed LULC layer that serves as inputs to the proposed PEM. The least cost distance path is calculated by giving each type of terrain a specific cost, as described in Table 4-9. Once all attributes of the LULC layer are given a cost, the layer is then converted to a raster of 0.5m cells by using the QGIS rasterize tool. This cell resolution was chosen to better match the contour of the structures. For cases where a cell covers two or more terrain types, the cell will assume the maximum cost. For instance, if a cell covers grass and part of a structure, the cell will default to the value of the structure since it has the highest cost.

4.3.1. Land Use

The land use layer, created in 2006 by the school of planning at UPR-RP and the Puerto Rico Planning Board, describes the type of terrain for the study area. This layer has a direct impact on the evacuation time. The land use layer is converted to the friction cost layer by giving each terrain type a cost. Each cost reflects how a certain terrain type influences travel time. For instance, high density urban area is given a cost of 1.2 due to the grass usually surrounding these areas; whereas water bodies are given a cost of 999, which automatically forces pedestrians to go around them in the event of an evacuation.

Table 4-9 The cost penalty for the friction cost surface land use layer based on terrain cost by (Soule & Goldman, 1972).

Type of Terrain	Cost	Type of Terrain	Cost	Type of Terrain	Cost	Type of Terrain	Cost
Artificial barrens	1.5	**Lowland moist abandoned and active coffee plantations**	1.5	**Mature secondary lowland moist noncalcareous evergreen forest**	1.8	**Salt water**	999
Emergent herbaceous non saline wetlands	1.8	**Lowland moist alluvial shrubland and woodland**	1.5	**Mature secondary moist limestone evergreen and semideciduous forest**	1.8	**Seasonally flooded herbaceous non saline wetlands**	1.8
Emergent herbaceous saline wetlands	1.8	**Lowland moist noncalcareous shrubland and woodland**	1.5	**Moist grasslands and pastures**	1.8	**Seasonally flooded herbaceous saline wetlands**	1.8
Fine to coarse sandy beaches, mixed sand and gravel beaches	2.1	**Lowland moist riparian forest**	1.5	**Moist limestone shrub land and woodland**	1.8	**Young secondary lowland moist alluvial evergreen forest**	1.5
Freshwater	999	**Lowland moist riparian shrubland and woodland**	1.5	**Rocky cliffs and shelves**	2.1	**Young secondary lowland moist noncalcareous evergreen forest**	1.5
High-density urban development	1.2	**Mangrove forest and shrub land**	999	**Salt and mudflats**	2.1	**Young secondary moist limestone evergreen and semi deciduous forest**	1.5
Low-density urban development	1.2	**Mature secondary lowland moist alluvial evergreen forest**	1.8				

4.3.2. Infrastructure

The infrastructure layer has two main purposes in the PEM. First, it serves as the emplacement of the family household units. Second, it serves as constraints for the evacuation path in the PEM, as mentioned in the land use section above. Although each structure has a unique ID and by default considered one family household unit, the model must consider that some structures represent condominiums that has multiple family units, some represent single family units, commercial or official buildings, some more have dual uses: commercial and residential (hybrids). Each scenario of the PEM uses specific categories of the infrastructure layers. The night time scenario uses the single and multiple family units, hybrids, hotels, and hospitals. The day time scenario uses the same layers as the night time scenarios, but commercial buildings and public venues are added.

Table 4-10 ACS Table showing the number of houses per household size per sub-county

	Number of Households				
Sector	**1-person**	**2-person**	**3-person**	**4+-person**	**Total**
Atalaya	102	87	41	67	297
Barrero	138	116	35	52	341
Calvache	222	289	56	215	782
Cruces	77	211	108	74	470
Ensenada	137	176	126	73	512
Jagüey	41	67	35	108	251
Pueblo	428	380	252	469	1529
Puntas	258	290	166	73	787
Barrio-Pueblo	105	100	30	92	327
Río Grande	109	139	67	142	457

4.3.2.1. Digital Cadaster

The digital cadaster layer provided by the Puerto Rico Planning Board allows the PEM to have a precise location for the infrastructure throughout the municipality of Rincón. Two layers were provided: one to identify residential and non-residential zones terrain classification, and another layer consisting of 7,759 polygons representing the structures inside the study area. A total of 1,676 structures are inside the tsunami evacuation zone (TEZ). The TEZ structures are further divided into commercial, residential, hybrid, public venues, critical and essential facilities. A map of the structures layer is shown in Figure 4-6. To update the structures layer in the TEZ, a recent

2017 image of Google maps was used as background and missing polygons were manually traced and added to the structures layer obtained from the PR Planning Board. A zone classification layer obtained from the Puerto Rico planning board is used to classify the commercial and residential structures inside the TEZ. Please refer to Figure 4-7 for the zone classification layer.

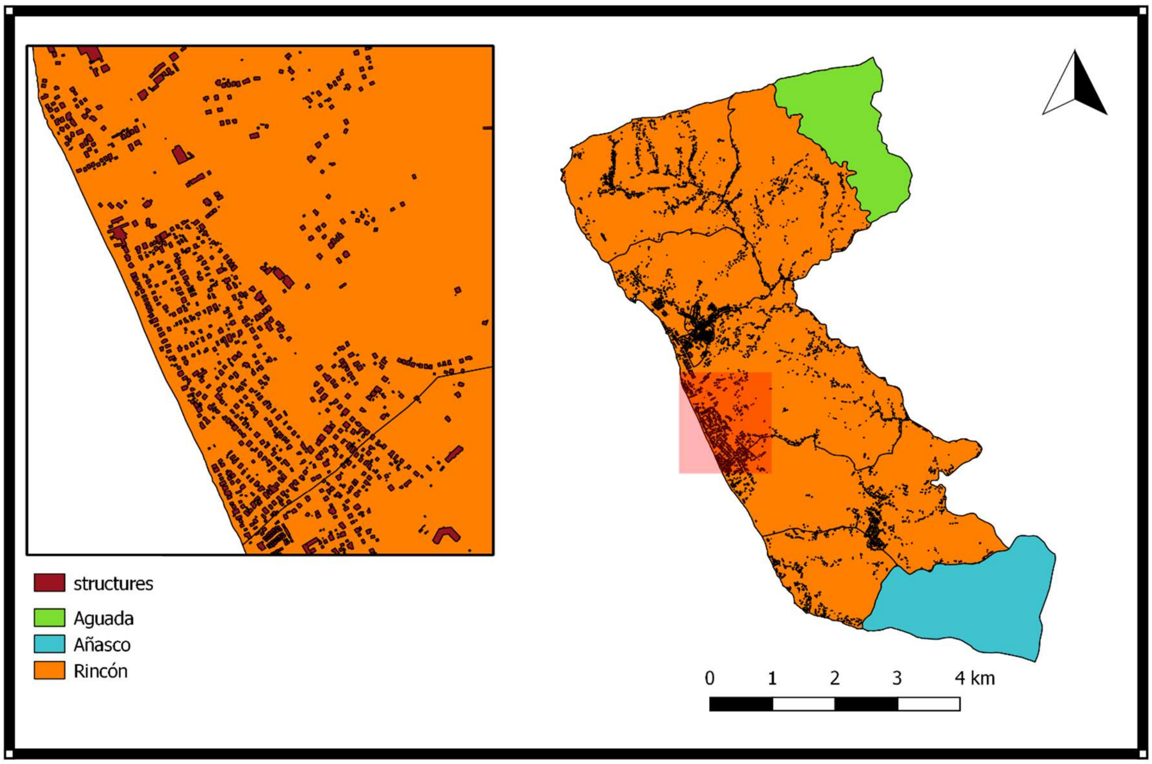


Figure 4-6 Overview of the structures layer in the study area.

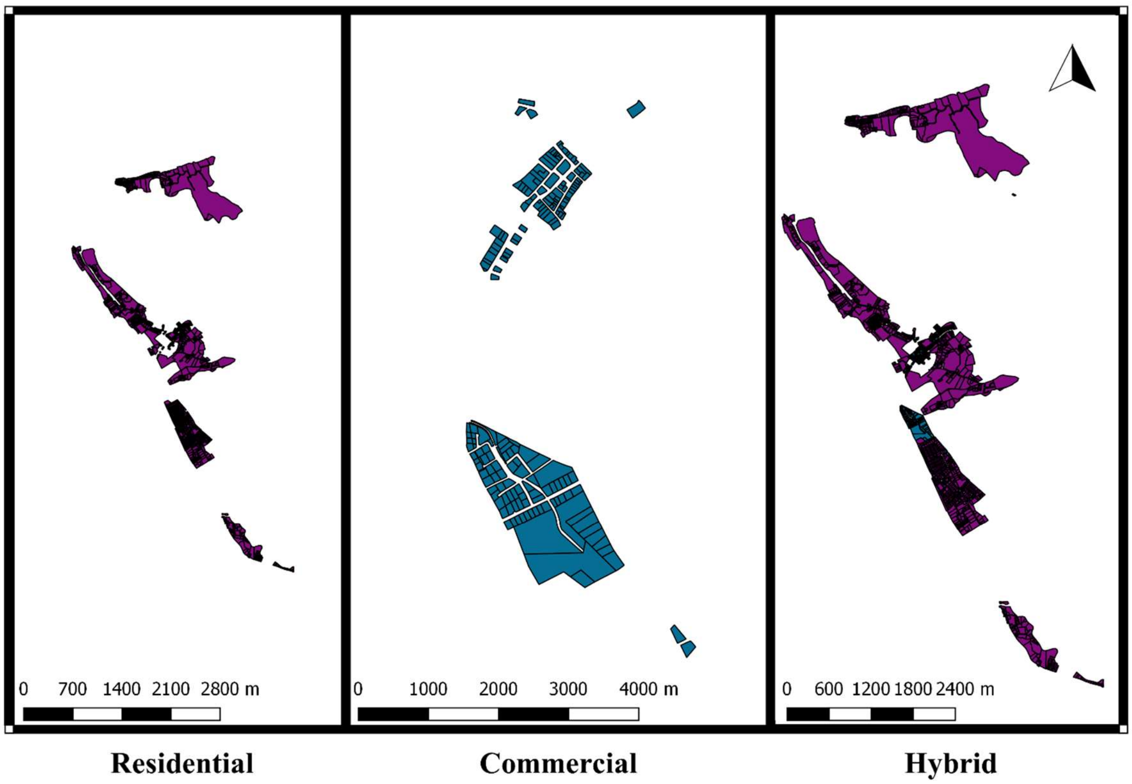


Figure 4-7 Infrastructure zone type layers.

After evaluating the data obtained from the PR Planning Board, it was noted that the data was not up to date and numerous data pre-processing tasks were required. In order to correct this issue, a joint effort was made by the research team to develop and use the ArcGIS Collector mobile phone application to create a geo-reference database of Rincón's infrastructure. The application was used to either map or manually update structures such as hotels, condominiums, businesses, hospitals, and so on. Along with the geo-location, additional information was collected such as the number of floors and number of apartments per floor in the case of residential buildings. Figure 4-8 shows screenshots of the ArcGIS application.

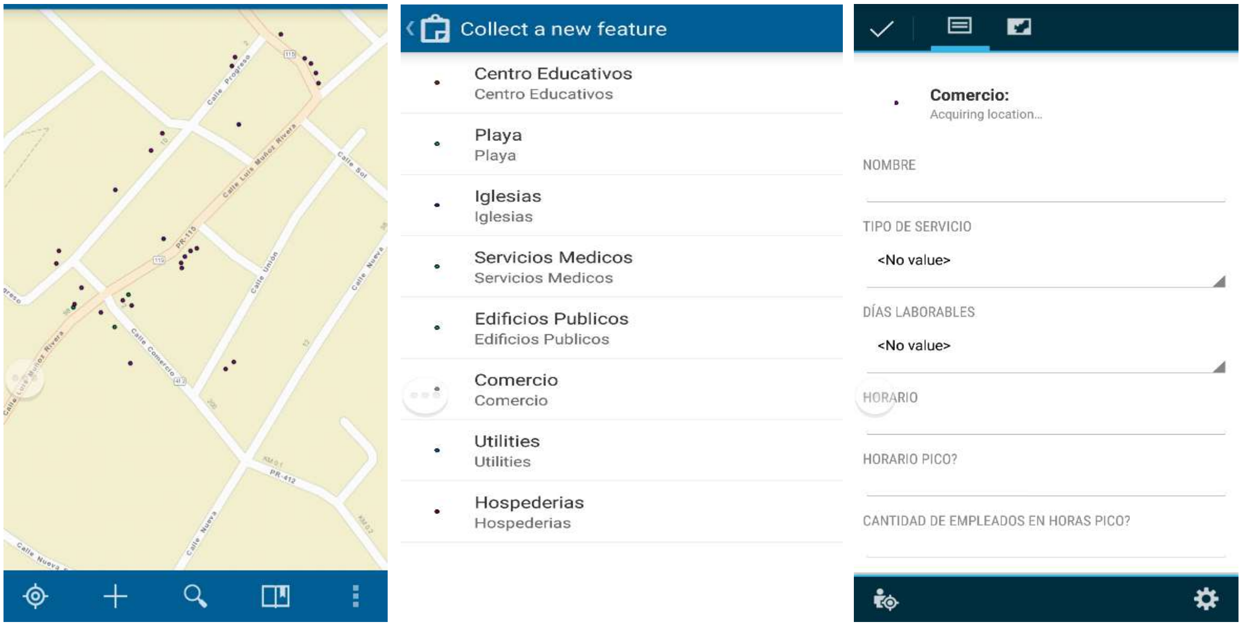


Figure 4-8 Screenshots of the ArcGIS collector app that was used to create a geo-referenced database of Rincón's infrastructure.

Once all data points were collected, the database allowed to separate the non-residential infrastructures into three main categories: critical and essential facilities and public venues. Please refer to Table 4-11 for the type of infrastructures that fall into each category.

Table 4-11 Infrastructure categories based on the nomenclature in Wood and Schmidtlein (2012)

Critical facilities	**Essential facilities**	**Public Venues**
Civil-defense facilities	Banks and credit unions	Aquariums
Fire stations	Courts and legal offices	Botanical gardens
National-security facilities	Gas stations	Colleges and universities
Police stations	Government offices	Historical place
Ambulance services	International-affairs offices	Historic place (NRHP)
Hospitals	Grocery stores	Libraries
Outpatient-care centers		Museums
Offices of physicians		Parks
Electric facilities		Religious organizations
Public-works facilities		Shopping centers and malls
Gas facilities		Sporting facilities
Radio and television facilities		Theaters
Waste-water and sewer facilities		

Hotels occupancy data obtained from the Puerto Rico Tourism Company was aggregated for the municipalities of Rincón and Añasco and, thus, several assumptions were made to be able to disaggregate the data. The underlying assumption here was that the total number of rooms in the municipality was going to be representative of the proportion of the total registrations in that municipality. That is, if one municipality has 25% more rooms than the other, then, it is assumed that municipality has 25% more hotel registrations as well. The analysis used to disaggregate the data was carried out using two sets of data: total number of rooms per hotel and hotel occupancy rates (Puerto Rico Tourism Company, 2015).

The data analysis revealed that Rincón has 75% of the total number of rooms. This percentage was then used to separate the occupancy rates of hotels in Rincón and Añasco. Table 4-12 presents the total occupancy for both municipalities in first 2 rows, and 75% occupancy for Rincón, in last 2 rows.

Table 4-12 Total occupancy for Rincón and Añasco in first 2 rows, and 75% occupancy for Rincón, in last 2 rows (Puerto Rico Tourism Company, 2015).

	2012						***2013***	
	July	**August**	**September**	**October**	**November**	**December**	**January**	**February**
Total registration	11600	7660	8596	6013	7644	6143	5904	5403
Total Occupancy Rate	0.73	0.52	0.54	0.47	0.53	0.50	0.53	0.60
Rincón Registration (75%)	8700	5745	6447	4509.75	5733	4607.25	4428	4052.25
Rincón Occupancy Rate (75%)	0.55	0.39	0.40	0.35	0.39	0.37	0.39	0.45

A custom R script was created to get the number of hotel occupants based on gender and age categories. A weighted random sample of 1 to 4 people with respective probabilities of 0.1, 0.5, 0.2, and 0.2 was generated and summed up to get the maximum total occupants per hotel based on the total number of rooms per hotel. These weights were chosen based on the assumption that two-person or two+-person hotels bookings are more common than one-person hotel bookings. This maximum number of occupants is then multiplied by Rincón's hotel maximum total occupancy rate of 55% resulting in an estimated number of occupants per hotel.

The sum of this estimation was, then, divided by age and gender using the data on the DP1 for all municipalities in PR. After removing Rincón's data from the DP1 table for all of PR, it was assumed that the majority of the tourism in Rincón corresponds to visitors from other parts of the island. The processed data yielded 51% female to 49% male occupants, as well as percentages of the age categories for each gender described in Appendix IV. The estimated hotel population is then multiplied by these percentages to obtain a hotel population based on gender and age categories. It is worth noting that, since dealing with percentages, the number of female occupants was randomly rounded up or down, and the number of male occupants is the difference between total occupants and female occupants. The age categories are then sampled based on their respective percentages, and assigned to the female and male occupants. Once done, the age categories of 65 and over are aggregated to form a single category of 65+ to match the PEM tables.

4.3.3. Roads Layer

Using the QGIS software, the roads layer for the TEZ area was downloaded directly from OpenStreetMap. A list of the classification of the roads layer can be found in Table 4-13. Apart from dirt track and unclassified roads, which were given a friction cost of 1.1, all other road classifications were given the lowest friction cost of 1. The roads layer has the lowest cost of travel. Whenever possible, evacuees are expected to stay on the roads network unless crossing an open-field area saves more time than staying on the roads. Please refer to Figure 4-9 for an overview of the roads networks.

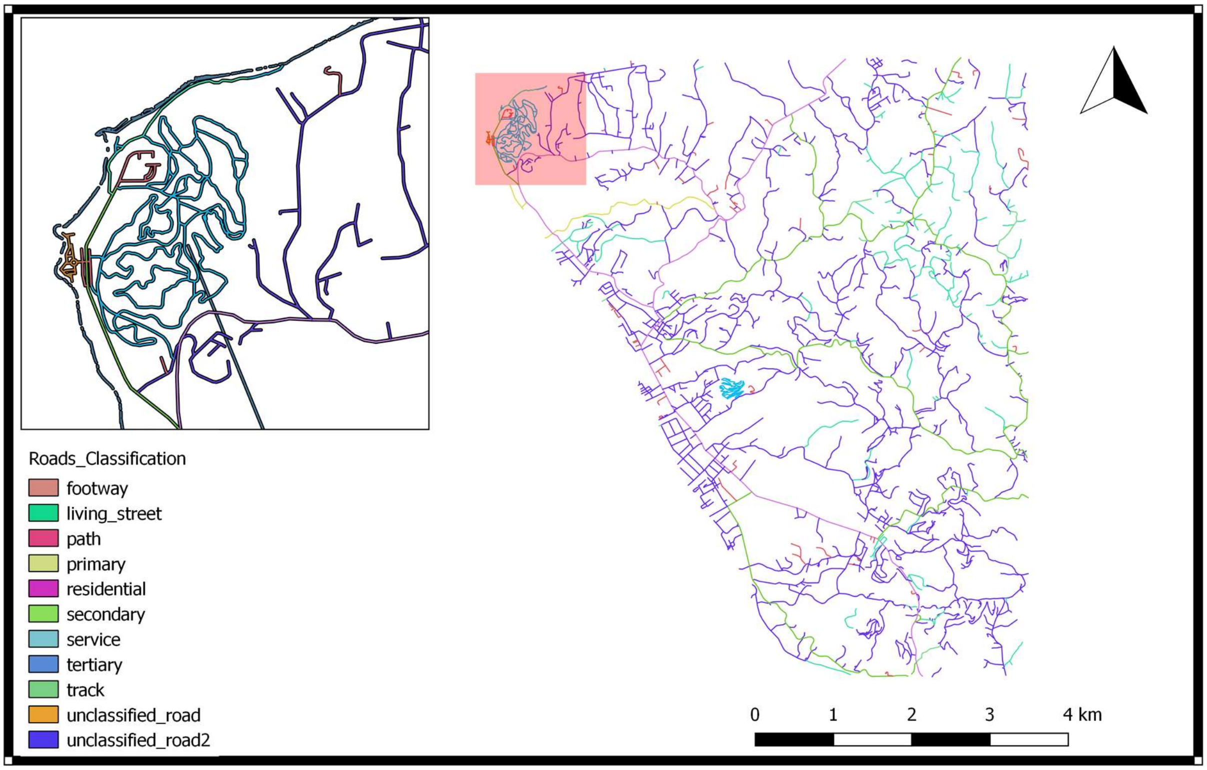


Figure 4-9 Overview of the road network in study area.

Table 4-13 Type of terrain classification and corresponding friction cost

Type of Terrain	Cost	Type of Terrain	Cost
footway	1	**service**	1
living_street	1	**tertiary**	1
path	1	**track**	1.1
primary	1	**unclassified_road**	1.1
residential	1	**unclassified_road2**	1.1
secondary	1		

The LULC is a combination of layers representing the terrain type and vegetation, different type of roads, and a layer representing the structures emplacement. To get friction cost, each category of the LULC layer is given a specific cost. These costs are based on Table 2-2 representing friction cost used by Soule & Goldman (1972) and Wood & Schmidtlein (2011). Figure 4-10 below represents the municipality of Rincón and a blow up of the area of Pueblo to appreciate the details of friction costs.

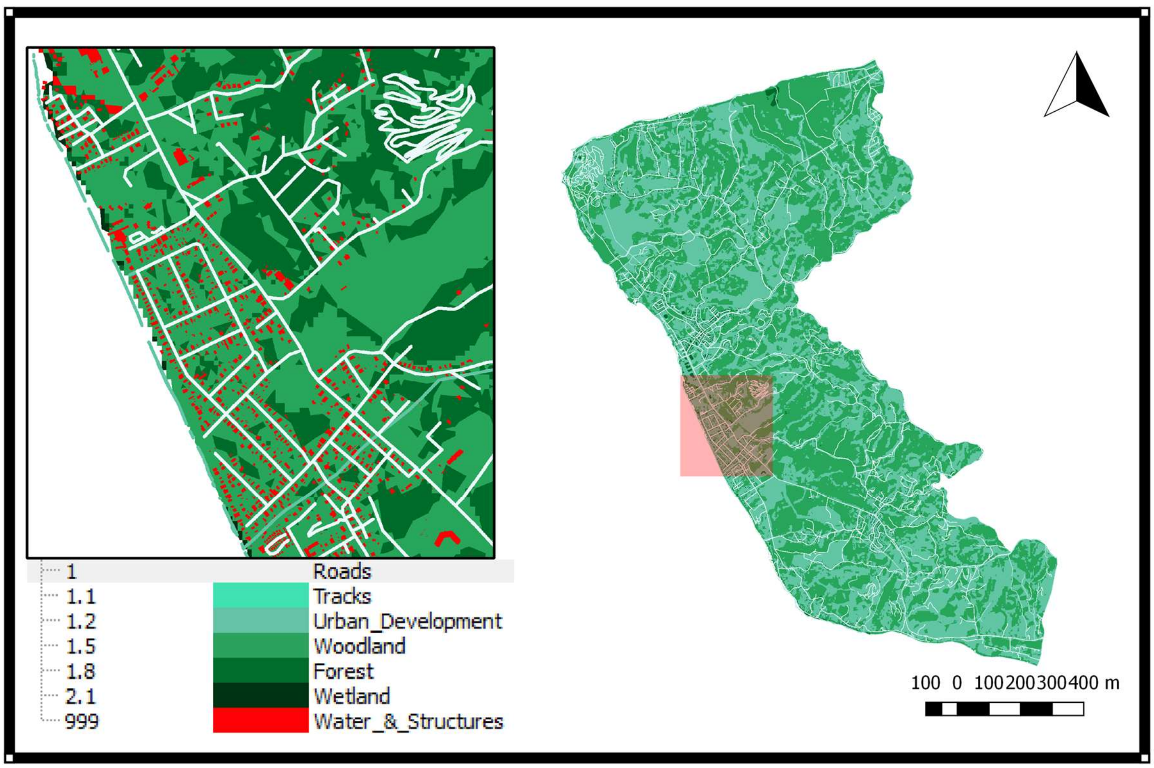


Figure 4-10 This Figure shows the division between the different type of terrain and their costs.

4.3.4. Digital Elevation Map (DEM)

DEM maps are used to calculate the slope of the evacuation area as a penalty to the travel time estimation where going downhill is faster than going uphill of the evacuee. The DEM for the study area was obtained from USGS at a resolution of 1/3 arc (roughly 10meters) (Taylor et al., 2015). The R.walk algorithm processes directly the values of the DEM. The anisotropic aspect is completely based on the DEM as the values of this layer are used to extract the slopes. Figure 4-11 shows a hillshade view of the Rincón's DEM map.

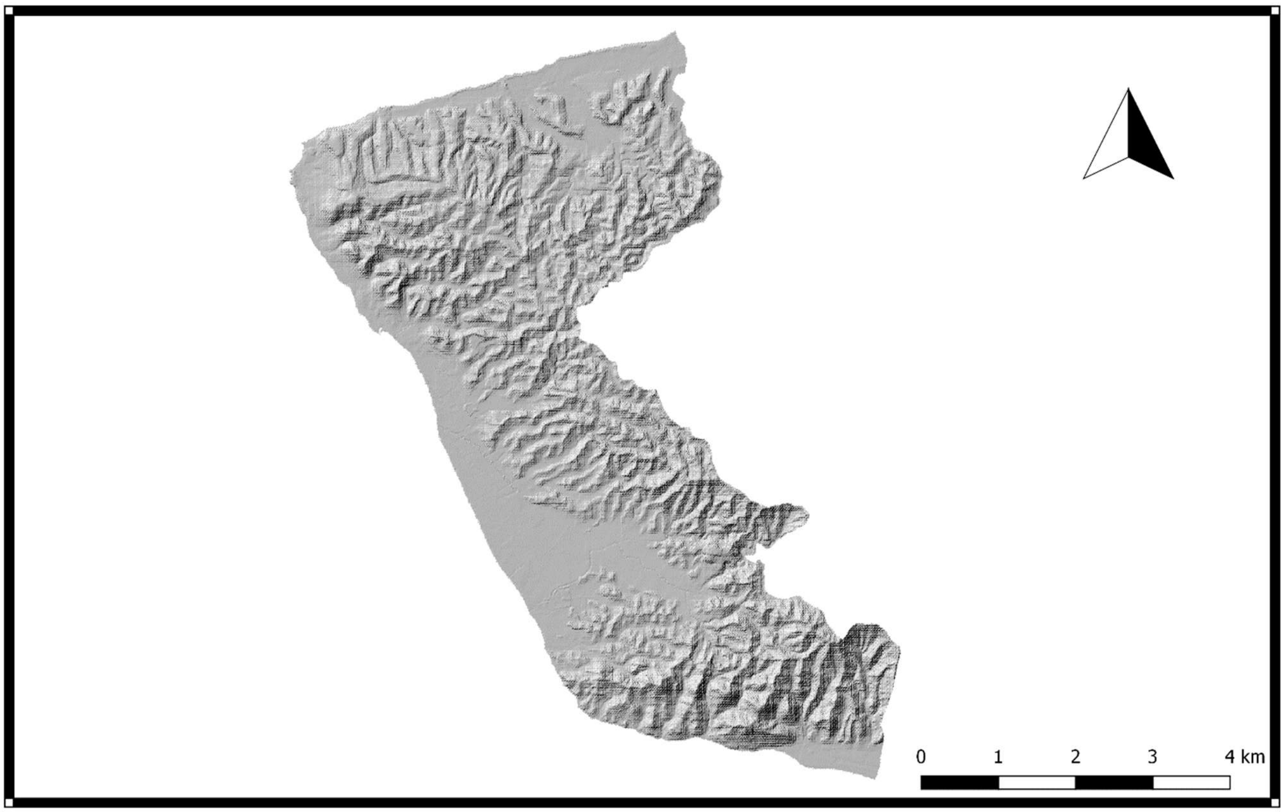


Figure 4-11 Rincón hillshade DEM map.

4.4 Pedestrian Evacuation Model (PEM)

The PEM is a multi-process where various tools and algorithms are used from within the QGIS and R software. The first step is to get the travel time or cumulative cost of travel. In this step, each scenario (e.g. slow walk, random run) is evaluated, and the respective evacuation speeds for each group are inputted into the model. This step requires the DEM layer, the LULC layer with the friction costs, and the starting points. Since the model is inversely calculating the cumulative costs (from safe area to TEZ), the inverse values of the DEM raster are used to get the correct slopes directions and values. The safe area raster, as explained in Section 4.1.2, can now be used as starting evacuation points. The algorithm uses the 0 values of the safe area (border line) to calculate the cumulative costs to every single non-null cell outside of the safe area. As explained previously, the knight's move option is used to have an expanded neighborhood which results in more precise results. The r.walk processing tool outputs two layers: cumulative cost for travel times and movement direction for travel paths.

Using the structures layer as overlay to the cumulative cost layer, the evacuation times can now be extracted for each building. Since each household unit structure covers several cells of the cumulative cost layer, zonal statistics tool is used to get the minimum value of the cumulative layers' cell touching each structure. This value represents the anisotropic travel time in seconds from each structure to the safe area. It is important to note that since structures cells have a very high cost in the LULC raster, the cumulative cost layer will output abnormal and very high travel times for these areas. The method chosen to correctly get the travel time from each structure was to buffer the structures' layer to 1 meter. This buffered structures' layer now covers approximately 2 extra LULC cells outside the perimeter of each structure. QGIS Zonal Statistics was then used to get the minimum cumulative cost value for each structure. This process was repeated 48 times to get the correct travel times for the 8 categorical groups and for each of the 6 evacuation speed scenarios. For the sake of visualization, r.drain tool is used to create evacuation routes based on the cumulative cost and movement directions layers. Figures 4-12, 4-13, and Figure 4-14 show screenshots of the r.walk, r.drain, and Zonal Statistics tools used in QGIS (QGIS Development

Team, 2017). The length of each evacuation route is calculated by adding an attribute field and applying the *$length* command. The *select by location* feature in QGIS was then used to attribute the evacuation routes' lengths to each structure.

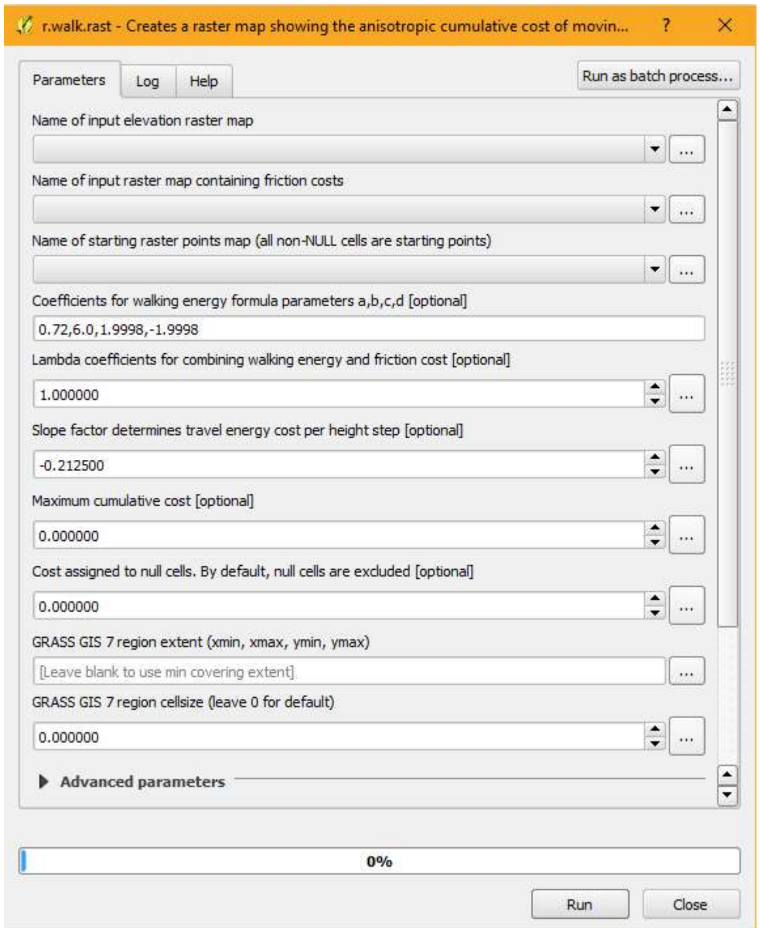


Figure 4-12 r.walk input screen of the QGIS software. Figure shows where the different layers are selected to get the cumulative cost and movement directions layers.

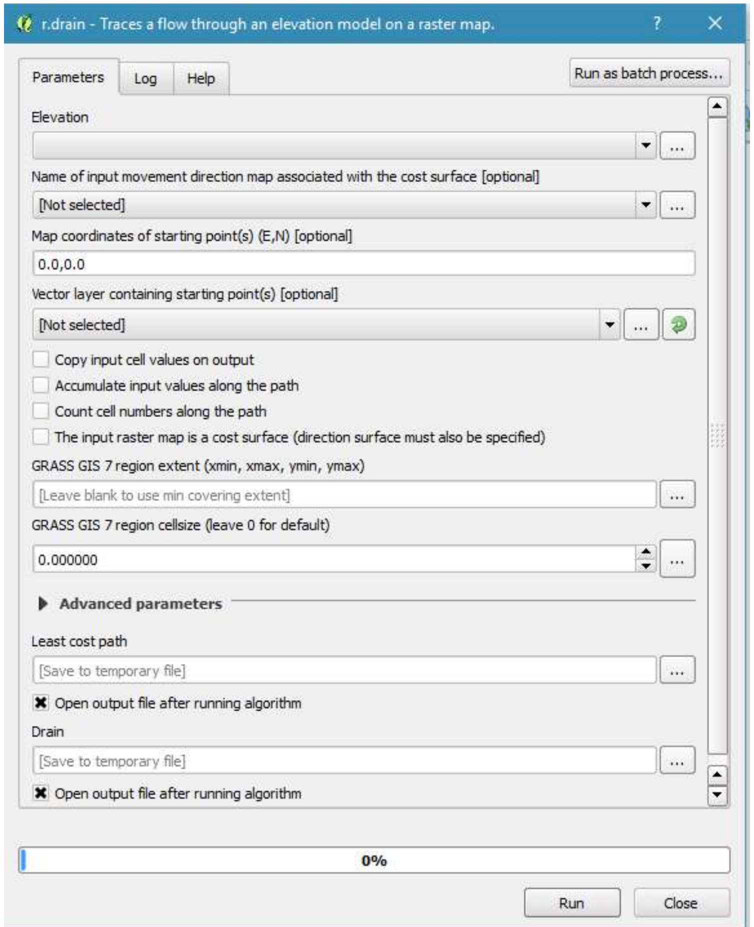


Figure 4-13 r.drain input screen. Figure shows where the cumulative cost and movement directions layers are used to get the least cost path of the PEM.

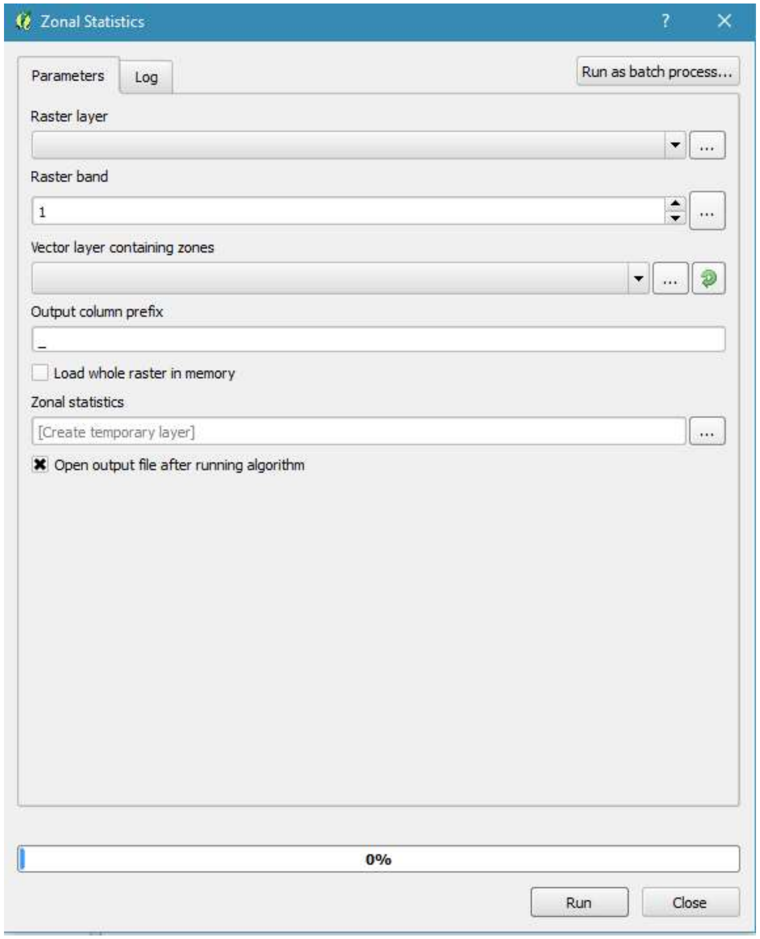


Figure 4-14 Zonal statistics tool. This allows to extract the cell values covered by each structure and print out descriptive statistics for each covered are

4.4.1. Evacuation Time

The total evacuation time (TTT) of this PEM is divided into three parts: anisotropic travel time (ATT), reaction time (RT), and fatigue time (FT). Combining these three times yield the formula:

$$TTT = ATT + RT + FT \tag{4-2}$$

ATT is provided by the cumulative costs layer of the PEM's outputs and is used to create evacuation maps (Figure 4-10) based on the time it takes to reach safety. These maps are useful to emergency managers to pinpoint areas where the population will most likely not have sufficient time to evacuate. The post processing of ATT allows to assign the appropriate travel time to each structure, and therefore to each family unit. RT and FT are then added to ATT to obtain the TTT for each family unit.

4.4.2. Reaction Time

Most PEMs come to an agreement that there is a certain delay (reaction time) at the start of an emergency evacuation. Numerous factors influence this type of delays. To minimize assumptions, stated evacuation responses were collected using the custom survey in Appendix I, and reaction times were calculated based on these responses and empirical research. It must be acknowledged that a stated reaction in a survey might not reflect the actual reaction of the individual at the time the flood or tsunami strikes. Nonetheless, it is still a big improvement over the current literature that strictly assumes how people will react without getting the population of interest involved in the process.

To the best of our knowledge, there is not any supporting literature that attributes reaction time to stated evacuation responses. The assumptions being described next are on a combination of work by Proulx and Fahy (1997), Yuzal et al. (2015), Mas et al. (2012), and Imamura et al. (2011).

Since the family is evacuating in one group, the stated response that most heavily penalizes travel time, in terms of its reaction time, is attributed to all the members of the same group. Please refer to Table 4-14 for the different reaction times based on the stated evacuation responses, the rationale used, and their sources.

Table 4-14 Reaction times based on the stated evacuation responses, rationale used, and their sources.

Category	Reaction time (seconds)	Rationale	Source
Do not evacuate	86400	**24hrs delay**	None
Contact Relatives first	63	**Office reaction with cool weather**	(Proulx & Fahy, 1997)
Evacuate immediately	36	**Office reaction**	(Proulx & Fahy, 1997)
Gather dependents	515	**Residential with bad alarm**	(Proulx & Fahy, 1997)
Help others	169	**Residential with good alarm**	(Proulx & Fahy, 1997)
Panic and Seek Help	300	**Institutional decision time**	(Yuzal et al., 2015)
Panic and evacuate	63	**Office reaction with cool weather**	(Proulx & Fahy, 1997)
Seek Evacuation Assistance	169	**Residential with good alarm**	(Proulx & Fahy, 1997)
Wait for Official Notification	480	**Institutional decision and notification times**	(Yuzal et al., 2015)

Mas et al. (2012) and Imamura et al. (2011) used the Rayleigh distribution to model departure times in hurricanes emergency evacuations. To relax the assumption of the reaction times presented in Table 4-14 , random samples are extracted from the Rayleigh distribution using the proposed reaction times as the scale parameter in the probability density function (PDF).

This PEM proposes a group-based evacuation, which assumes all members of the group evacuate together and, thus, share the same evacuation response. The model first attributes a response to everyone based on age and gender. It, then, selects each family household unit and gives all members the stated response of the agent that will result in the highest penalty.

4.4.3. Fatigue Model

The outputs of the r.walk algorithm provides the first estimation of the evacuation travel times. Many PEMs either stop at this step or consider various types of delays before the start of evacuation. This PEM goes a step further by considering reaction time as well as another important aspect of physical work–*fatigue*. In the efforts to make a realistic and accurate PEM, fatigue is introduced as a cost related to the distance traveled. The literature supports that for distances and travel times higher than 1,500 meters and 3.5 min, respectively, a fatigue factor can be calculated using the work by Riegel (1981).

The majority of Rincón's topography being mountainous, reduces the size of the inundation areas. Since the TEZ rarely covers distances of over 1,000 meters, the 1.5 km distance criterion is relaxed to consider distances greater than or equal to 1 kilometer. Using Equation (2-6), presented in Section 2.5, a fatigue time is calculated which will be added the anisotropic time of the PEM.

$$t = ax^b, \qquad (4\text{-}3)$$

where t = time in minutes, a = constant of relative speed, x = distance obtained from the length of the evacuation routes, and b = group median fatigue factor as presented in Section 2.5.

The r.drain tool from QGIS tool outputs an evacuation path for each structure inside the TEZ. The length of each evacuation path is calculated and used as distance in Equation 4-3. The relative speed factor is a constant that varies depending on the sport. In Riegel (1981), different relative speed constants are presented for running events. This work applies the constant of relative speed for female runners ($a = 2.598$) to all agents. This constant of relative speed represents a conservative approach to estimate fatigue, as it corresponds to the 20th percentile of the running constant of relative speeds described in the work by Riegel (1981).

In order to obtain the travel time with fatigue, Equation 4-3 is used by first calculating travel time with fatigue factor equal to 1 (indicating no fatigue effect). Using the same a and x values, travel time is calculated again with the fatigue factor corresponding to the agent. The difference between these two times represent the time penalty to be added to the anisotropic PEM time as in:

$$FT = ax^{b_1} - ax^{b_2}, \quad (4\text{-}4)$$

where FT = fatigue time to be added to PEM results, b_1 = median fatigue factor for each categorical group, and b_2 = 1.

This calculation is independent to the evacuation times calculated in the PEM and, therefore, the before and after fatigue effect can be evaluated in the sensitivity analysis, described in Section 4.4.5.

4.4.4. Population to Safety

Once TTT is attributed to each family, the number of family units and subsequently number of people to safety can be determined. Mercado and McCann (1998) explained that tsunami waves up to 18 feet could have reached Rincón in as little as 5 minutes. This time is used as the first cut-off to estimate the population at or under 5 minutes. Since the tsunami origin and strength depends on the earthquake epicenter and magnitude, cut-off times of 5 to 15 minutes were also considered. Lastly, cut-off times of over 15 minutes are analyzed and the families in this category most likely will not reach the safe area before the tsunami waves reach them. The estimation is done by using the unique structure ID for each household units. The count of unique structure IDs gives the number of families, whereas the count of unique people ID gives the number of people.

4.4.5. Sensitivity Analysis

Two main scenarios are being presented, day-time vs. night-time. The day-time scenario presents the case where commercial buildings are occupied by employees, schools are occupied by the dependent population, hotels have floating population, and residentials have the unemployed population. The night-time scenario presents the case where there are no employees nor students but only residents and hotels population. These two scenarios are connected by the fact that some structures shelter both residents and employees, and hotels and hospitals always have occupancy. These structures will always be present in the model no matter the scenario.

For the sensitivity analysis, first a macroscopic map with color-coded evacuation time is presented. These maps are based on the ATT and can be compared under different scenarios: slow and fast walk, slow, median, fast, and random run. Secondly, under the same scenarios, microscopic times are evaluated for the day and night time evacuation models. The 6 different evacuation speeds for ATT, RT, and FT present 18 different results of the PEM and they can provide valuable insight to Rincón's emergency response personnel.

5 CHAPTER - RESULTS

This chapter presents the different results of the proposed PEM, including some of the processed input data such as the family household distribution and infrastructure. The models for the aforementioned inputs were run ten times, and one of the replicates without any errors was selected. Table 5-1 shows the results of the different runs and the results presented in this chapter are based on run 6.

Table 5-1 Assignment errors for 10 replicates of the population assignment model. Assignments based on replicate 6 were used.

Run	Population Errors	Household Errors
1	0	0
2	0	38
3	0	0
4	0	0
5	0	56
6	0	0
7	0	0
8	0	93
9	0	0
10	0	0

5.1 Infrastructure

As mentioned in Section 4-3, the different type of infrastructure inside the TEZ were manually classified using QGIS. The classification results are presented in Table 5-2. The classification types used in this PEM are: apartment and condos, hotels, hybrid (both commercial and residential), and residential.

Table 5-2 Classification and count of structures inside the TEZ

Classification	Count
Apartments	255
Condos	21
Public	31
Hotels	17
Hybrid	17
Commercial	152
Residential	2078
Hospital	1
School	19
Other critical	12
Other essential	38

5.2 Agent Creation

5.2.1. Households

The multi-agent aspect of this PEM is based on the population input. Close to 15,000 people were assigned to structures within Rincón, but only 5,856 agents of those are based inside the TEZ and, thus, correspond to agents in the PEM. The distribution of these agents at the sub-county level is described in Table 5-3. This population was, then, used to create groups representing family households as presented in

	Households			**Condominiums**		
Sub-County	**F**	**M**	**Total**	**F**	**M**	**Total**
Barrero	161	152	313	0	0	0
Barrio Pueblo	133	131	264	34	29	63
Calvache	340	326	666	0	0	0
Pueblo (Córcega)	980	940	1920	15	16	31
Ensenada	311	273	584	173	151	324
Puntas	108	80	188	39	40	79
Rio Grande	2	1	3	0	0	0
Grand Total	**2035**	**1903**	**3938**	**261**	**236**	**497**

Table 5-4. Once the agents inside the TEZ are selected, the model creates additional households for the apartments inside the condominiums. Since the model had already attributed

one group of agents for each condominium, these agents are distributed to the apartments, and more agents are extracted from the safe area population.

Table 5-3 Distribution of resident population inside TEZ based on gender at the sub-county level.

	Households			Condominiums		
Sub-County	**F**	**M**	**Total**	**F**	**M**	**Total**
Barrero	161	152	313	0	0	0
Barrio Pueblo	133	131	264	34	29	63
Calvache	340	326	666	0	0	0
Pueblo (Córcega)	980	940	1920	15	16	31
Ensenada	311	273	584	173	151	324
Puntas	108	80	188	39	40	79
Rio Grande	2	1	3	0	0	0
Grand Total	**2035**	**1903**	**3938**	**261**	**236**	**497**

Table 5-4 Groups of agent created per sub-county based on household size

	Household size					
	1	**2**	**3**	**4**	**5**	**Grand Total**
Barrero	50	94	48	172		364
Rincón Pueblo	43	78	54	152		327
Calvache	68	164	54	380		666
Pueblo (Córcega)	292	564	411	1060	5	2332
Ensenada	114	232	234	328		908
Puntas	47	52	102	96	5	302
Rio Grande			3			3
Grand Total	**614**	**1184**	**906**	**2188**	**10**	**4902**

5.2.2. Hotel Agent Creation

As part of the population input, this PEM also models the hotels and condominiums population. The hotels agent creation is based on the number of rooms and occupancy data, and the condominiums agent creation is based on the number of apartments per condominiums and household size limits. Once the needed number of agents per hotel is known, the model creates agent based on US Census tables. Since the hotel population is considered as non-Rincón residents, the Rincón data was deleted from the US Census tables and the percentages for males and females was calculated for each age category. These percentages were inputted into the model as probabilities for each age and gender categories. Based on these parameters, a random sample of the number of hotels agents is pulled and distributed to each room. Please refer to Figure 5-1 for the respective agent creation count for the hotels, condominiums, and households.

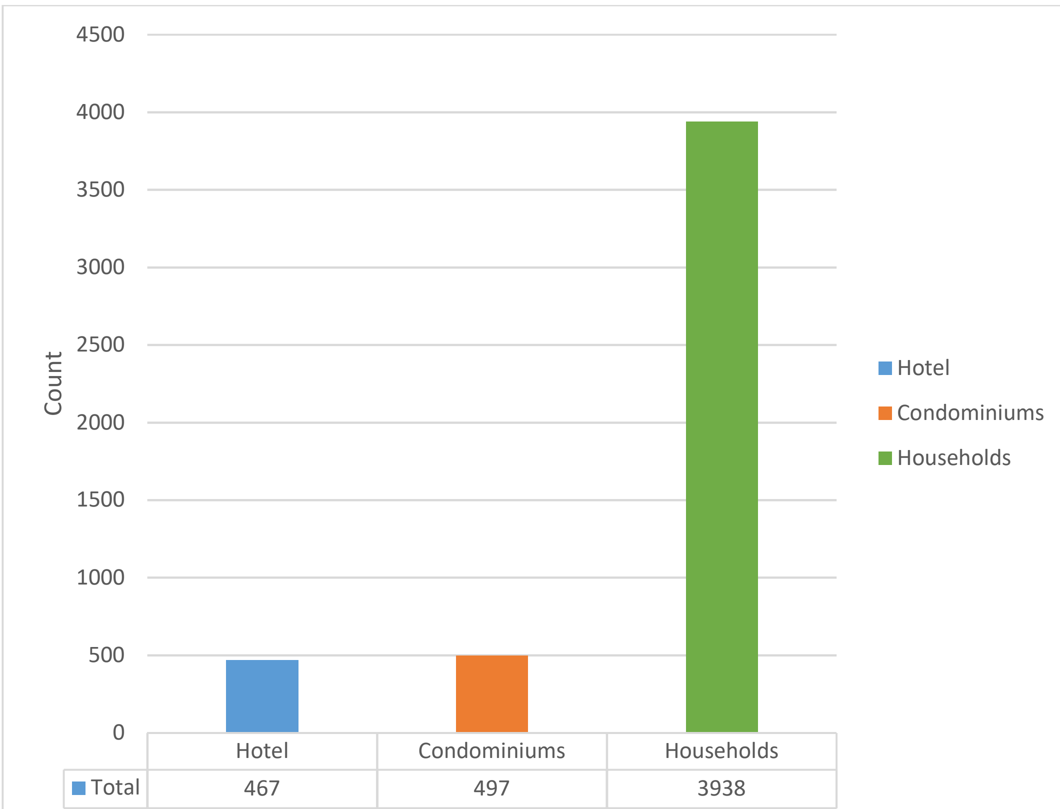


Figure 5-1 Agent count per structure classification in TEZ.

5.2.3. Condominium

It was previously mentioned in Section 4.2 that the condominiums population was created based on visual estimation of the number of apartments per condominium and setting a limit of up to 5 persons per condominium. Once the apartments created, the unique identifiers for each condominium are changed, and the apartments are now given their respective unique identifier. It is worth noting that while adding the condominiums population rises the total population inside the TEZ, the total population count in Rincón remains unchanged since the condominiums population is selected from the outside TEZ population. Please refer to Table 5-5 for details on the agent count per condominium.

Table 5-5 Agent Count per condominium

	Sub-County				
Row Labels	**Barrio Pueblo**	**Corcega**	**Ensenada**	**Puntas**	**Grand Total**
Blue Bay Inn			6		**6**
Casa Marina			9		**9**
Chalet_del_Mar			55		**55**
Ocean Terrace				21	**21**
Ocean View Paradise				6	**6**
Pelican Point				11	**11**
Pools Beach Apartment				2	**2**
Puerto Bahia			62		**62**
Punta Taino				32	**32**
Residential Santa Rosa	63				**63**
Rincon Bay Villas			31		**31**
Rincon by the Sea			60		**60**
Rincon Ocean View			51		**51**
Rincon Wave View			50		**50**
Sea BeachVillage		31			**31**
Villa Ocean Mist				7	**7**
Grand Total	**63**	**31**	**324**	**79**	**497**

5.2.4. Employees

As mentioned in Section 4.2, for the day time scenario, employees were modeled using B23001 Census table (U. S. Census, 2015). The number of employee agents needed was sampled out of the agent population distribution created for the night time scenario. Please refer to Figure 5-2 for the details on employee count per sub-county.

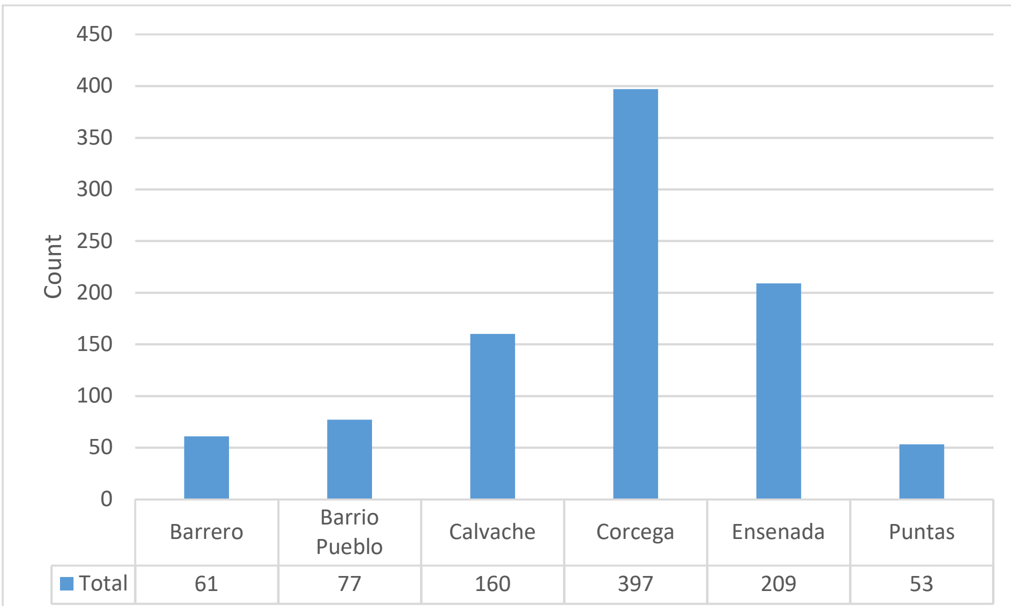


Figure 5-2 Employee count per sub county

5.2.5. Students

As previously mentioned in Section 4.2, student' agents population is sampled out of the family distribution. Using Rincón' students data from Noodle (2017) and Eladrel Technologies LLC (2017), the numbers of students and teachers were estimated for each school. The model only creates a student' agent population for the Jorge Seda Crespo school since it is the only school inside the TEZ. Please refer to Figure 5-3 for more detailed information in the number of students attending that school and their home sub-county.

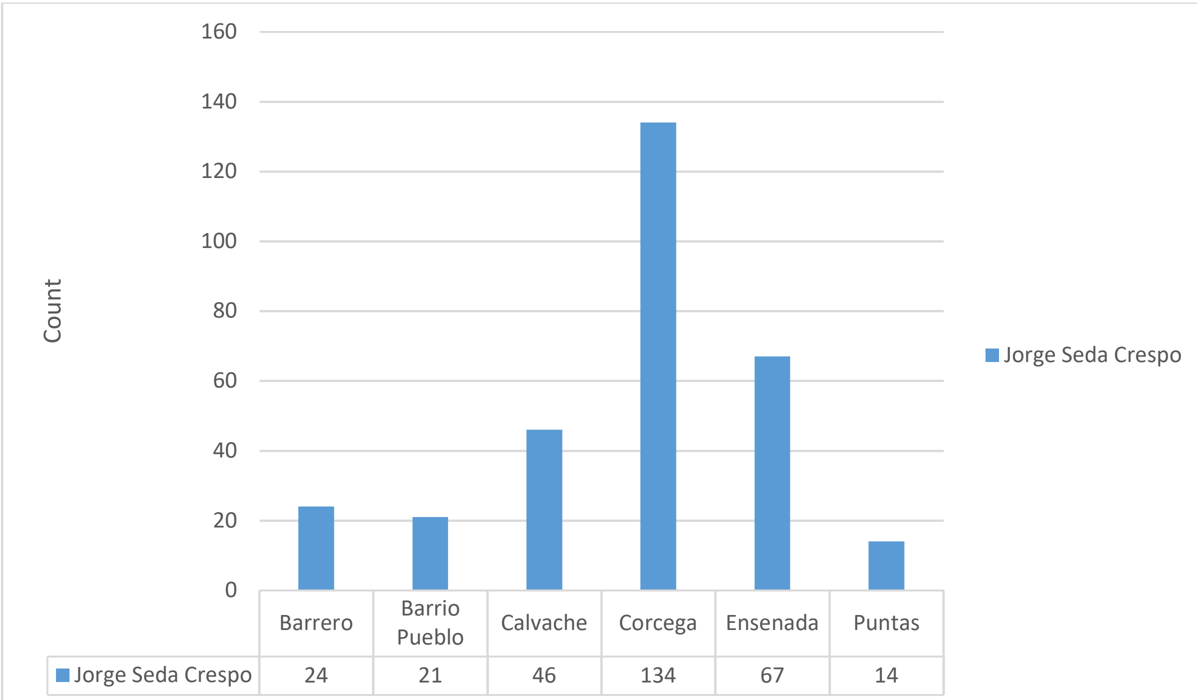


Figure 5-3 Number of students in Jorge Seda Crespo school. Students are divided by their home sub-county.

5.3 PEM Results – Night Scenario

5.3.1. Evacuation Map

The PEM outputs the ATT for every group at different speed scenarios. Since the slowest travel speed will yield highest travel times, this speed is considered the worst-case scenario. Table 5-6 shows a comparison of the slow-walk speeds and the consequences of reaction delay and fatigue penalties. A travel time map, generated using the combined slow walk speed is presented in Figure 5-4. This map shows in red, areas (hotspots) where slow travel time are over 15 minutes to reach safe area, in yellow travel times of 5 to 15 min, and in green travel times of 5 minutes or less. The area to the North, Río Grande, has no structures and therefore no agents were placed in this area. Nonetheless, Pueblo (Córcega) is the second hotspot, closer to the South. This area, is the most populated area in Rincón and has one of the highest average evacuation time. Please refer to Table 5-6 for a list of the different times.

Table 5-6 Average time comparison of the average for the slow walk speed for the different levels of evacuation times, anisotropic (ATT), reaction (RT), and fatigue (FT) for each one of the sub-counties.

Sub-County	ATT	$ATT + RT$	$ATT + RT + FT$
Barrero	10.94	12.32	2.96
Calvache	26.26	28.14	4.26
Ensenada	12.53	13.63	18.42
Pueblo (Córcega)	24.24	25.72	12.00
Puntas	6.42	7.33	5.54
Rincón Pueblo	7.92	9.56	2.95
Río Grande	0.00	0.79	0.64
Grand Total	**26.26**	**28.14**	**9.92**

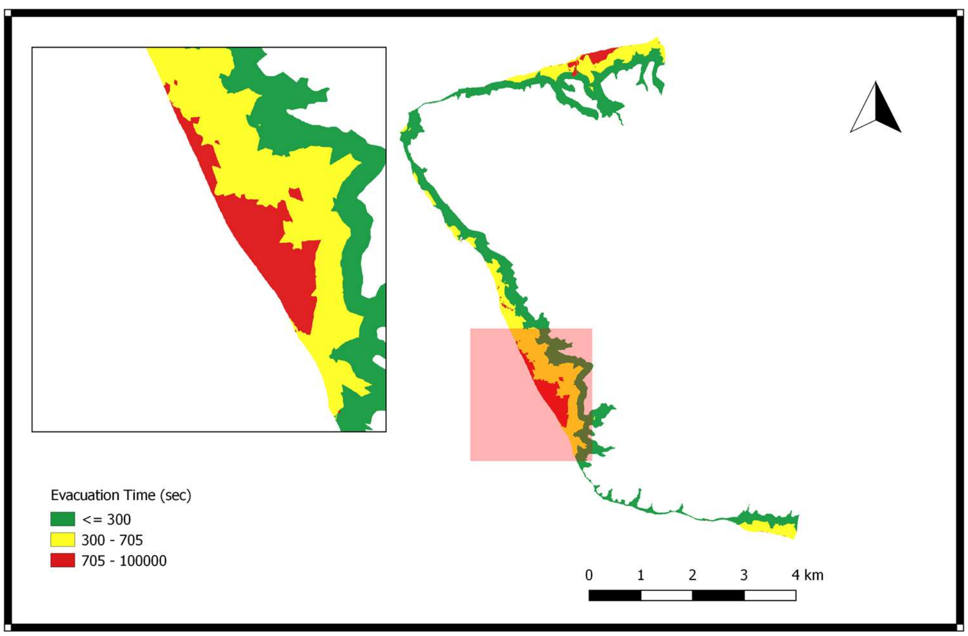


Figure 5-4 Map of the study area divided into three evacuation time categories.

Using the output of the QGIS r.walk tool, evacuation routes were generated for each structure. Please refer to Figure 5-5 and Figure 5-6 for more details on how the evacuation routes tend to follow the roads unless cutting through open fields will result in a reduction of the total travel time.

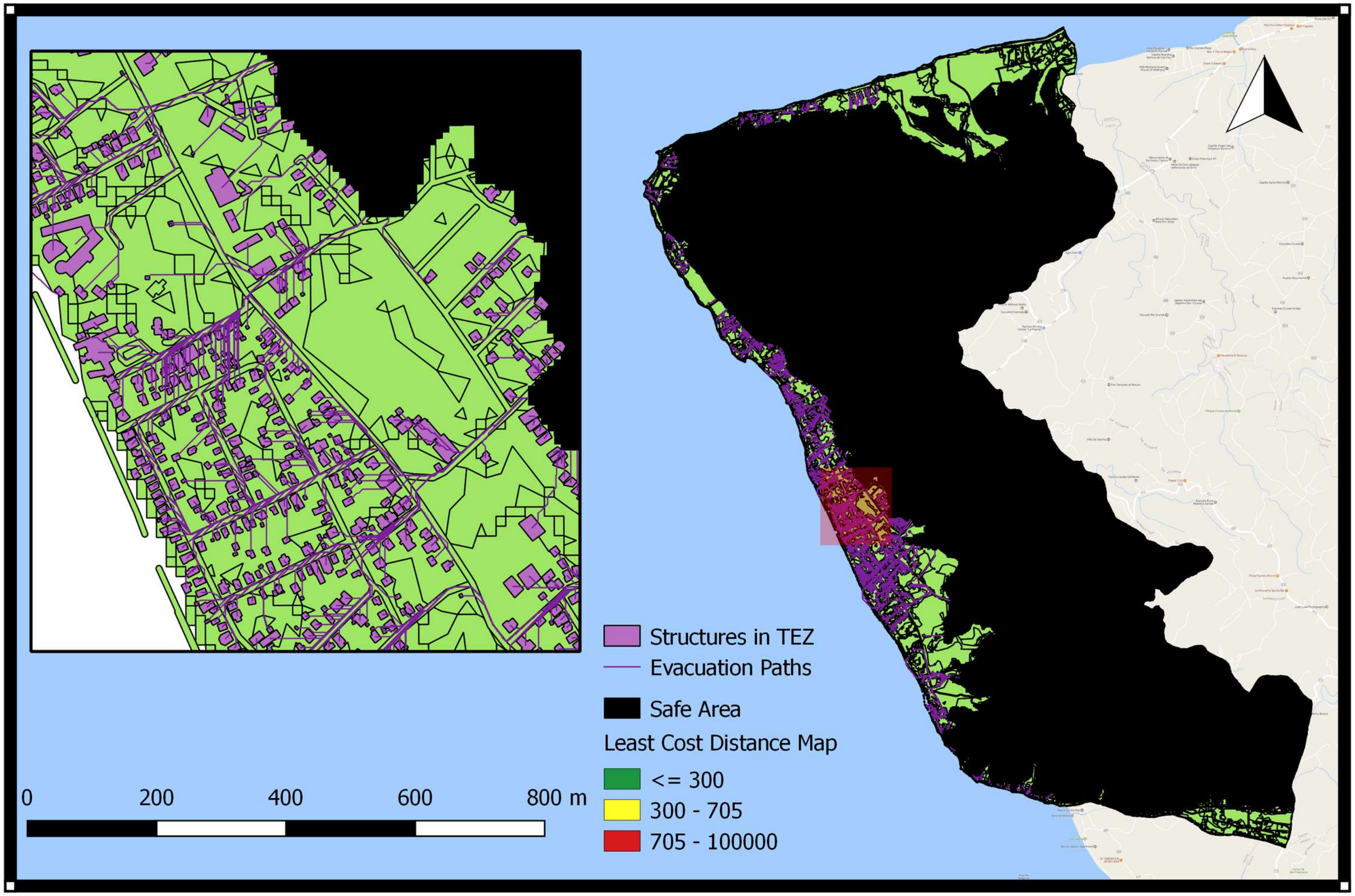


Figure 5-5 Sample representation of evacuation paths for each structure inside the TEZ.

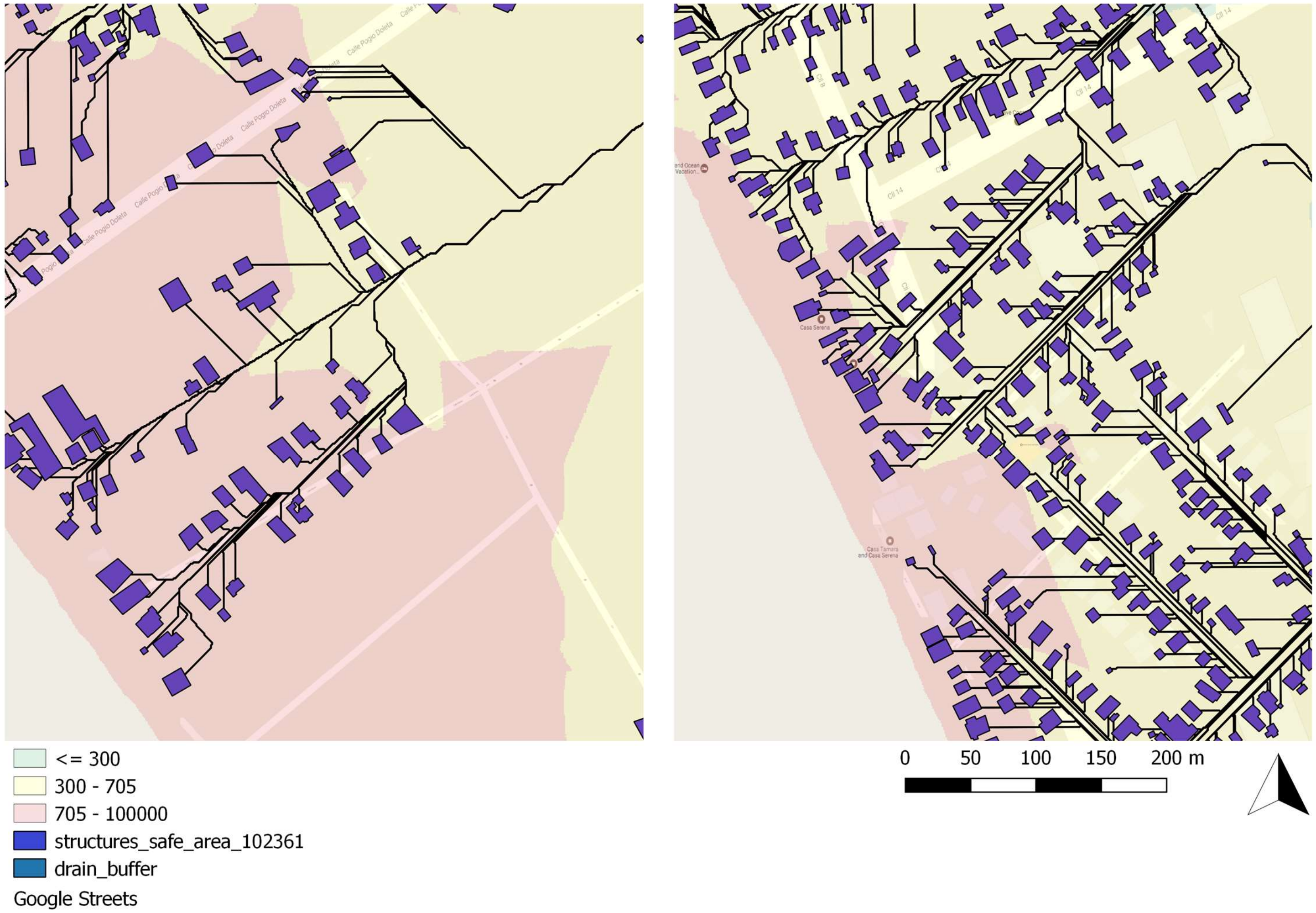
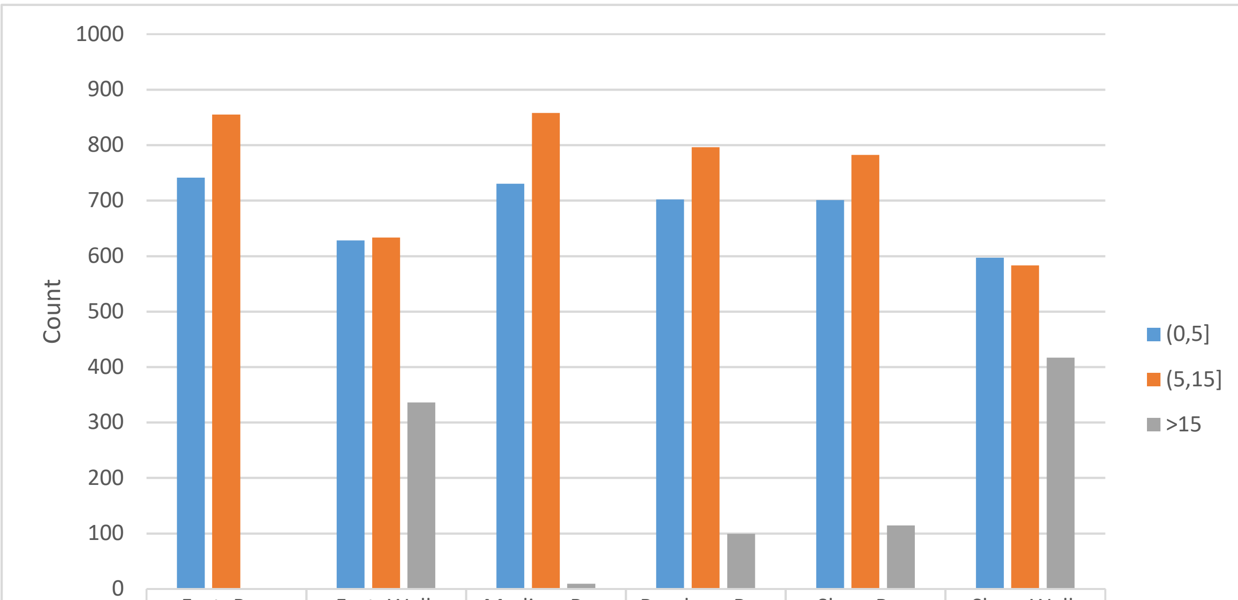


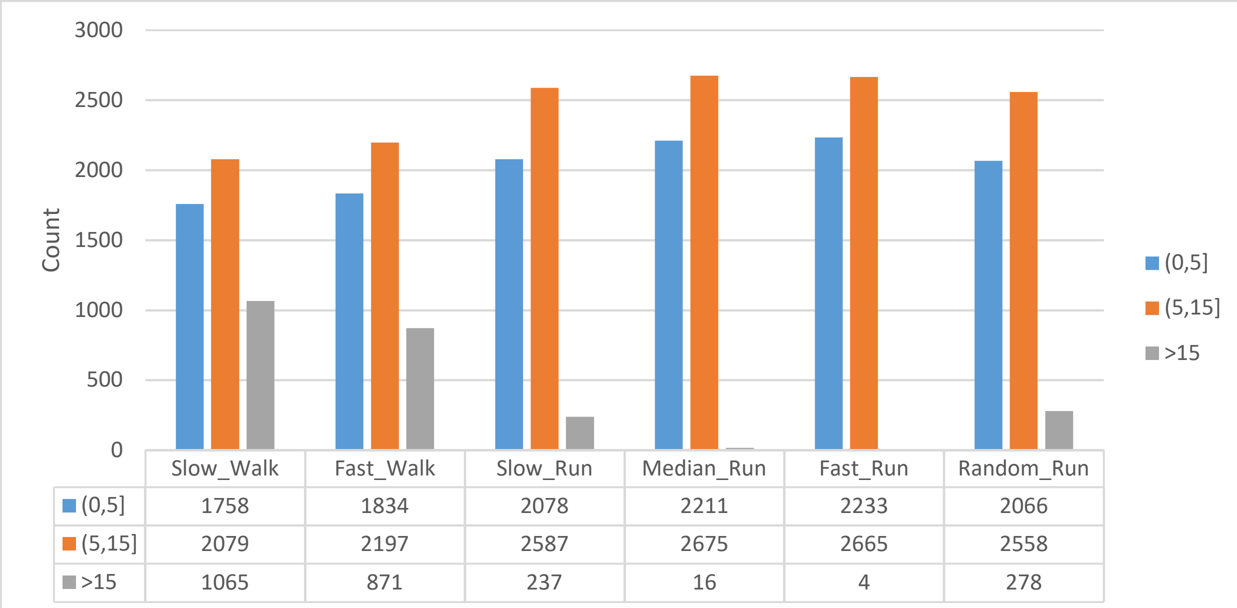
Figure 5-6 Evacuation routes of some structures in areas that take over 5 minutes to reach safety based on the slow walk speed.

Figure 5-7 and Figure 5-8 show the respective group and agent count for the ATT based on the 6 different speed categories. The number of agents reaching safety is clearly increasing as the evacuation speed increases.



	Fast_Run	Fast_Walk	Median_Run	Random_Run	Slow_Run	Slow_Walk
(0,5]	741	628	730	702	701	597
(5,15]	855	633	858	796	782	583
>15	1	336	9	99	114	417

Figure 5-7 Anisotropic travel time (in minutes) depicting grouped agents at different speed scenarios.

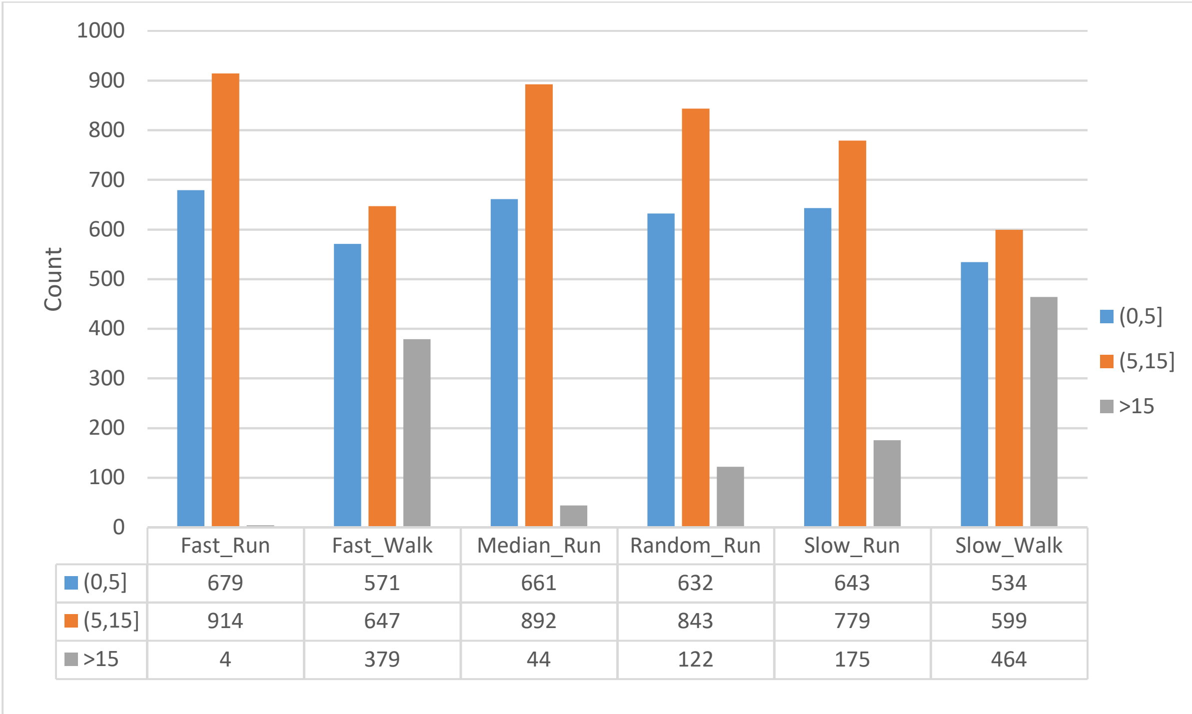


	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	1758	1834	2078	2211	2233	2066
(5,15]	2079	2197	2587	2675	2665	2558
>15	1065	871	237	16	4	278

Figure 5-8 Anisotropic travel time (in minutes) depicting individual agents at different speed scenarios.

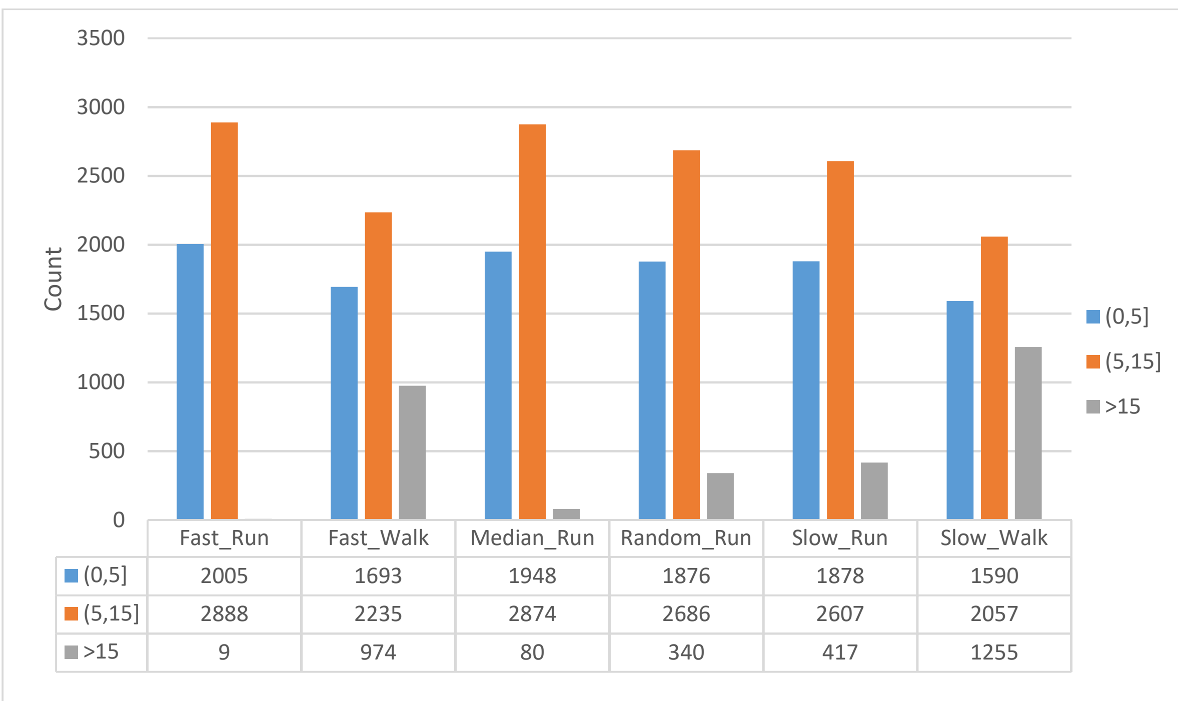
5.3.2. Reaction Time (Anisotropic + Reaction)

As explained in Section 4.4.2, reaction times delay were calculated based on the different stated responses and supporting literature (Proulx & Fahy, 1997; Yuzal et al., 2015; Mas et al., 2012). Figure 5-9 and Figure 5-10 shows respectively the count of agents per speed category to reach safety for each time brackets. A clear drop can now be observed in the number of agents reaching the safe area in 15 minutes or less. For instance, in less than 15 minutes, 4,624 agents reached the safe area with no penalties added for the slow walk scenario. When added a reaction delay, only 3,647 agents reached the safe area in 15 minutes or less, a 21.13% decrease.



	Fast_Run	Fast_Walk	Median_Run	Random_Run	Slow_Run	Slow_Walk
(0,5]	679	571	661	632	643	534
(5,15]	914	647	892	843	779	599
>15	4	379	44	122	175	464

Figure 5-9 Anisotropic travel time + reaction delay (in minutes) for grouped agents at different speed scenarios.

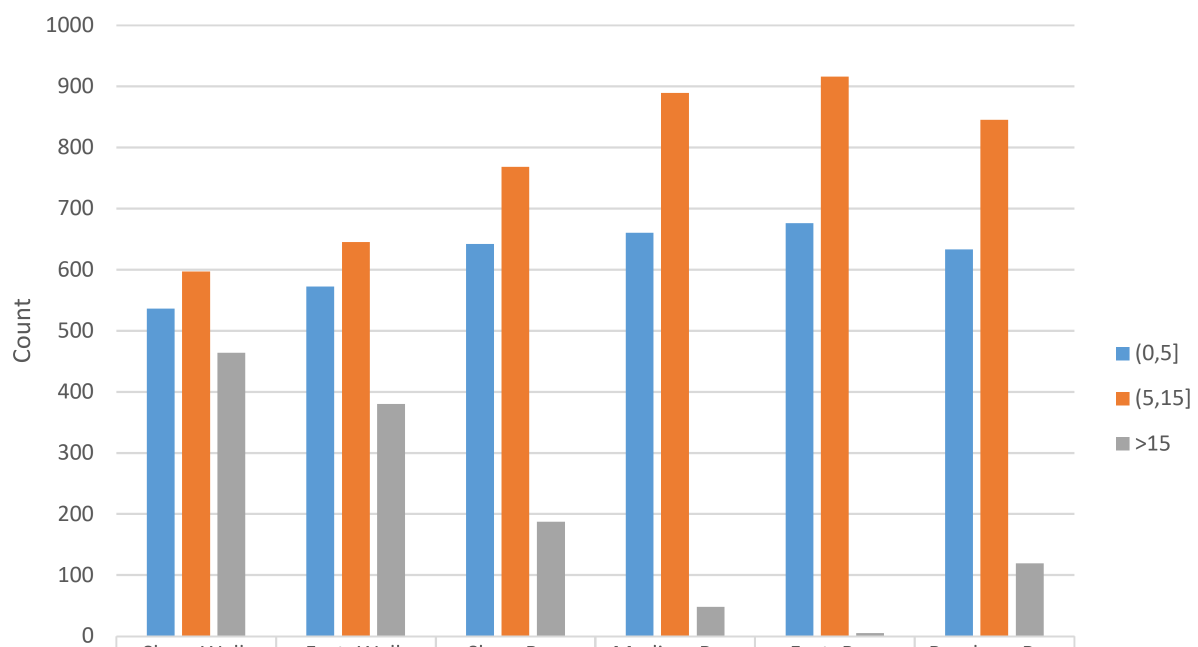


	Fast_Run	Fast_Walk	Median_Run	Random_Run	Slow_Run	Slow_Walk
(0,5]	2005	1693	1948	1876	1878	1590
(5,15]	2888	2235	2874	2686	2607	2057
>15	9	974	80	340	417	1255

Figure 5-10 Anisotropic travel time + reaction delay (in minutes) for individual agents at different speed scenarios.

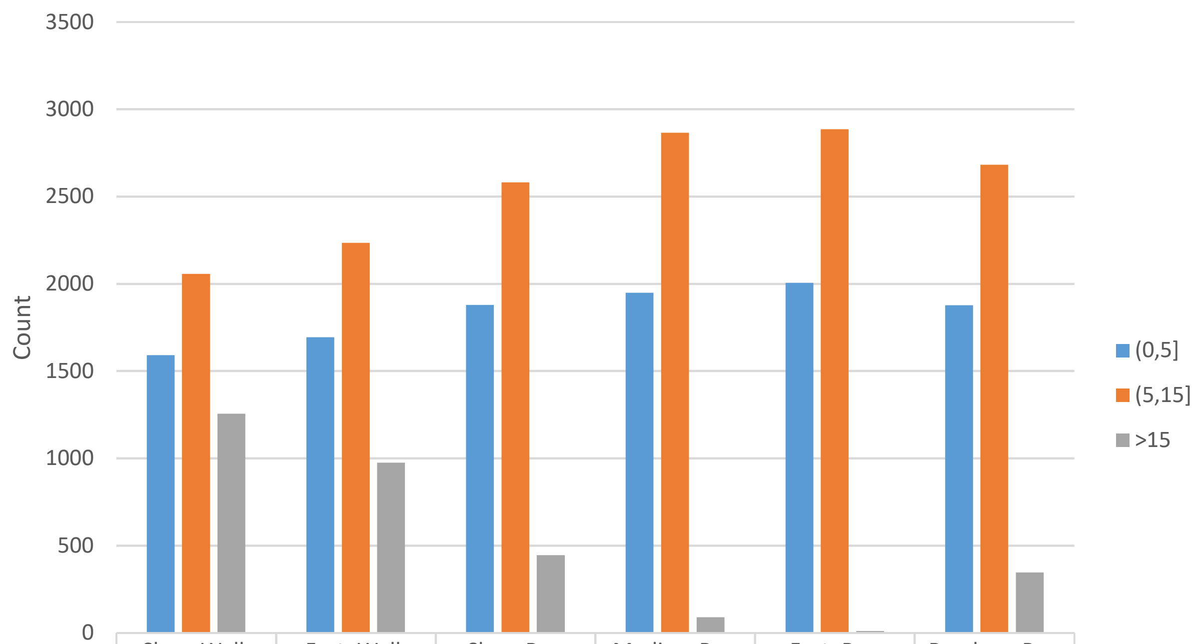
5.3.3. Evacuation Time (Anisotropic + Reaction + Fatigue)

In Section 4.4, the equation for the total travel time was presented to be equal to the sum of the ATT, the RT, and the FT. Since the fatigue penalty only applied to evacuation distances of 1,000 meters or more and a limited number of agents fit that category, the fatigue effect is not as pronounced as the reaction delay effect. Nonetheless, the slow run scenario shows that 3,647 agents reached the safe area in 15 minutes or less when fatigue and reaction delays are added compared to 4,485 with just the reaction delay. A difference of 838 agents. Figure 5-11 shows the count of the grouped agents that reached the safe area under the different speed scenarios. Figure 5-12 show the count of people to reach the safe area under the same attributes.



	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	536	572	642	660	676	633
(5,15]	597	645	768	889	916	845
>15	464	380	187	48	5	119

Figure 5-11 Count of groups to reach safety after considering fatigue and reaction time at different speed scenarios. Intervals shown depict evacuation time in minutes.



	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	1590	1693	1878	1948	2005	1876
(5,15]	2057	2234	2580	2865	2886	2681
>15	1255	975	444	89	11	345

Figure 5-12 Count of individuals to reach safety after considering fatigue and reaction time at different speed scenarios. Intervals shown depict evacuation time in minutes.

5.3.4. Population to Safety

Figure 5-13, Figure 5-14, and Figure 5-15 show respectively the ATT, RT, and FT time for the agents in the model. These figures show clearly the differences in the number of agents reaching safety after each time constraint is added. The highest differences are observed in the 5 minutes or more categories since after the time penalties, more people move from one time category to the next.

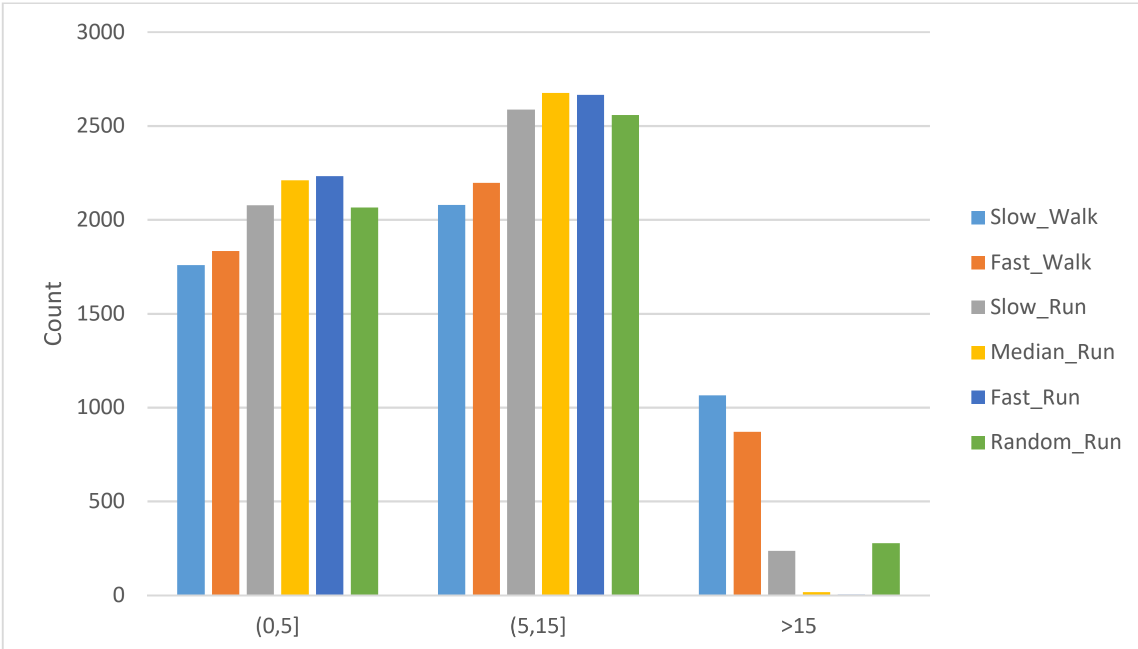


Figure 5-13 Count of agents to reach safety under different evacuation speeds scenarios based on anisotropic travel time (ATT).

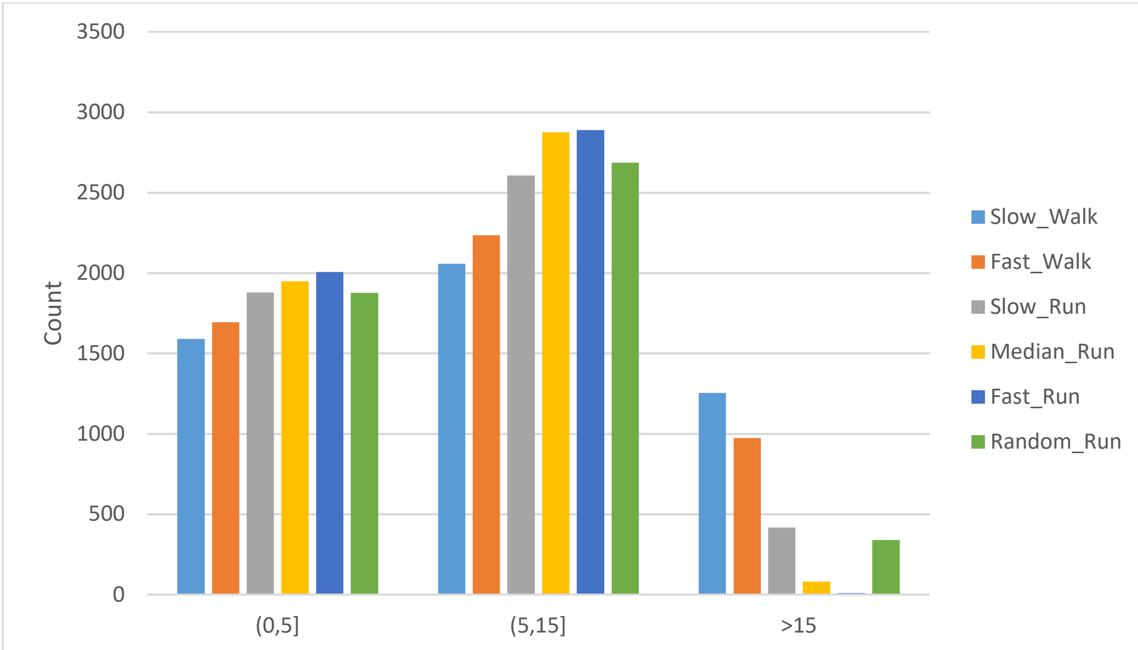


Figure 5-14 Count of agents to reach safety under different evacuation speeds scenarios based on anisotropic travel time (ATT) and fatigue time (FT).

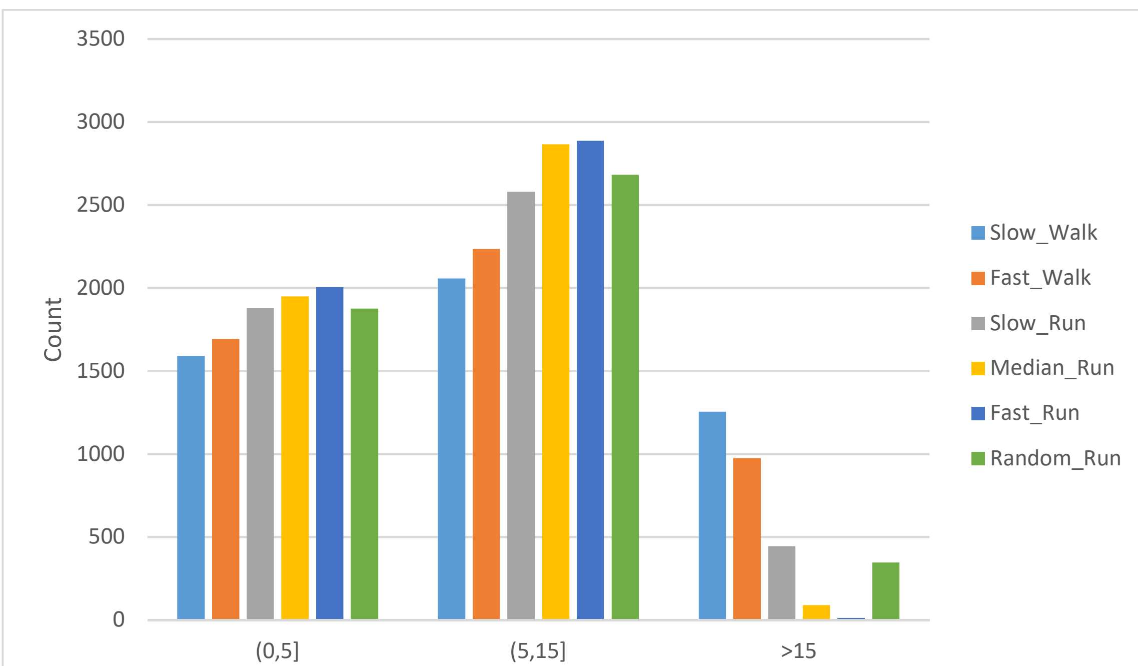


Figure 5-15 Count of agents to reach safety under different evacuation speeds scenarios based on total travel time (TTT), which includes fatigue time (FT) and reaction time (RT).

5.4 PEM Results – Day Scenario

Section 5-3 shows the results of a night time scenario where most of the population is at home, businesses, and schools are closed. This section presents the day time scenario where there are less people at home, but employees are at work and schools are open. The following results show the classification of the population (Figure 5-16) and their evacuation time.

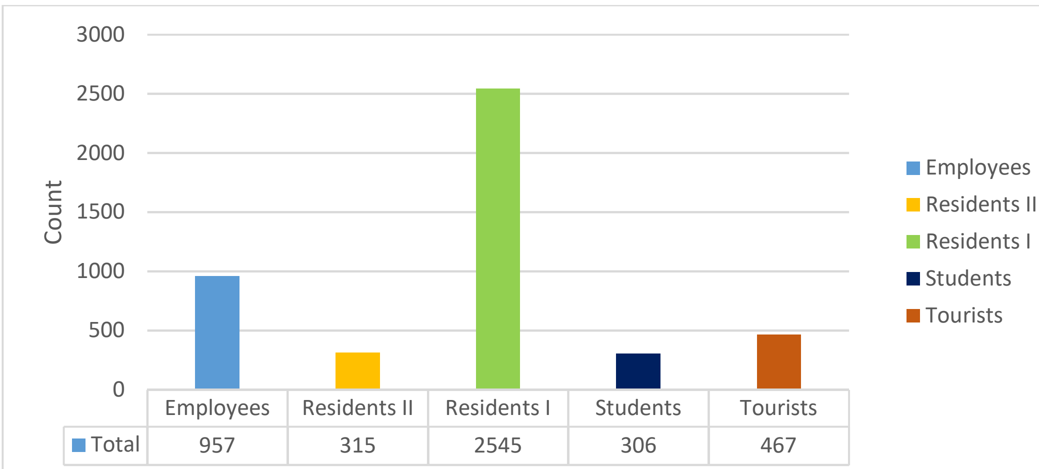


Figure 5-16 Population distribution for the day time scenario and the agent classification.

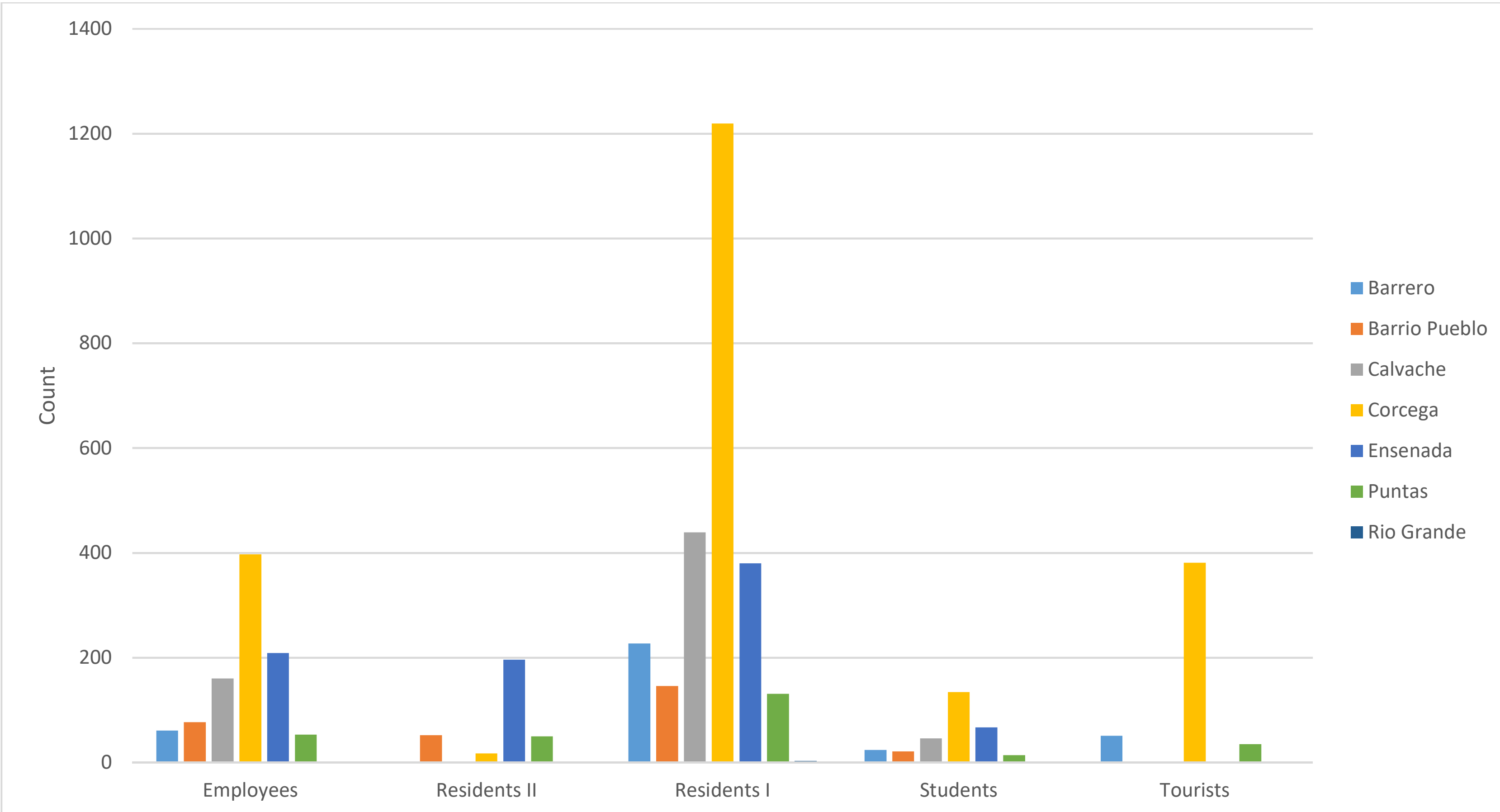
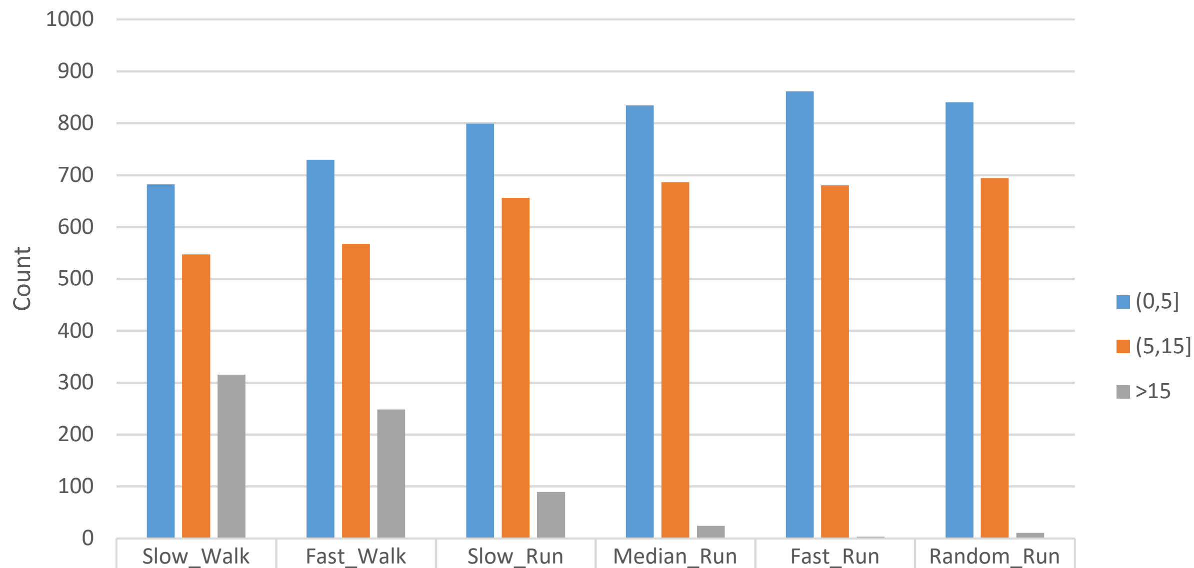


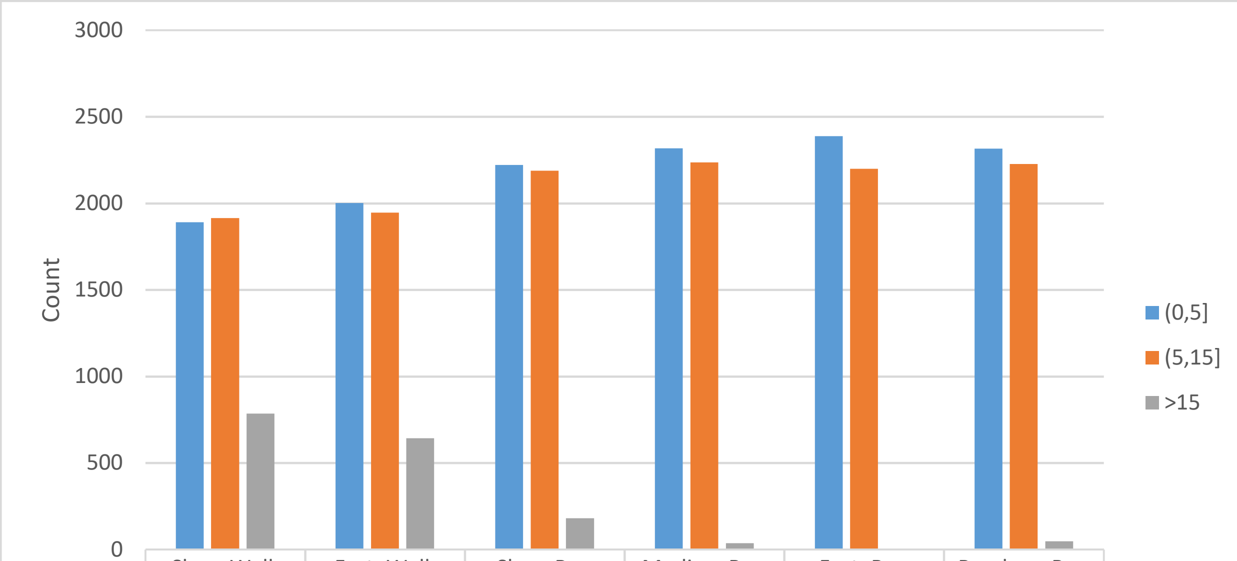
Figure 5-17 Classification of the agents' distribution on a sub county level

Figure 5-18 and Figure 5-19 show the respective group and agent count for the day time scenario of the ATT based on the 6 different speed categories. The worst case scenario represented by the slow walk shows 1,891 agents reached the safe area in 5 minutes or less, compared to 2,316 agents for the best case scenario or fast run, a 22.47% increase.



	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	682	729	799	834	861	840
(5,15]	547	567	656	686	680	694
>15	315	248	89	24	3	10

Figure 5-18 Anisotropic travel time output of the PEM specifically showing for groups at different speed scenarios.

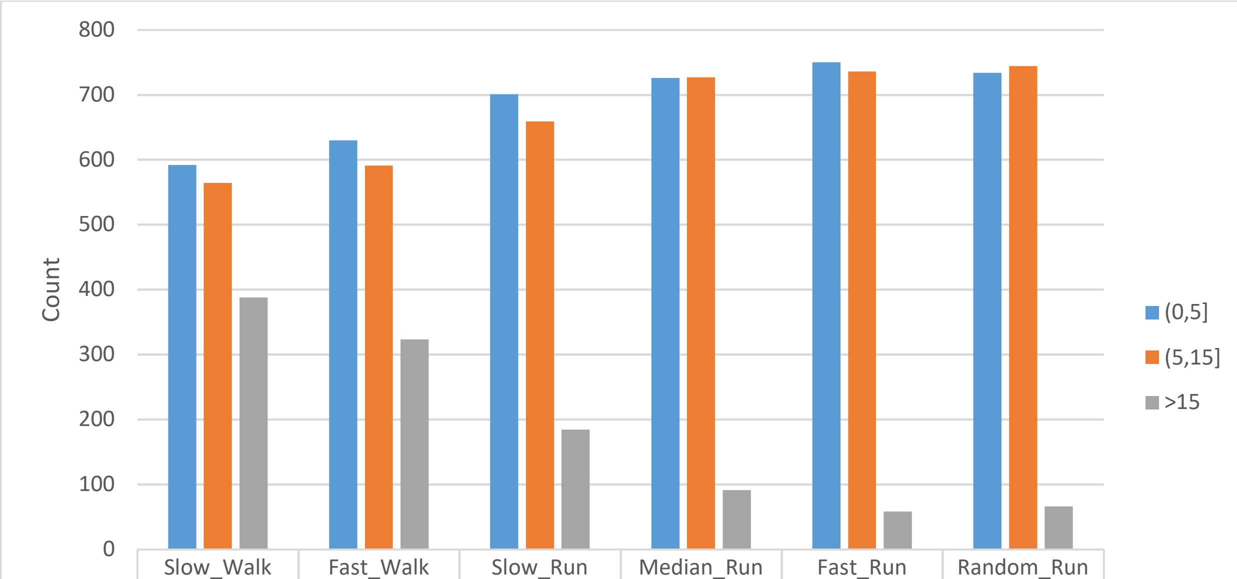


	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	1891	2002	2222	2317	2387	2316
(5,15]	1914	1946	2188	2236	2199	2226
>15	785	642	180	37	4	48

Figure 5-19 Anisotropic travel time output of the PEM specifically showing the result for individuals at different speed scenarios.

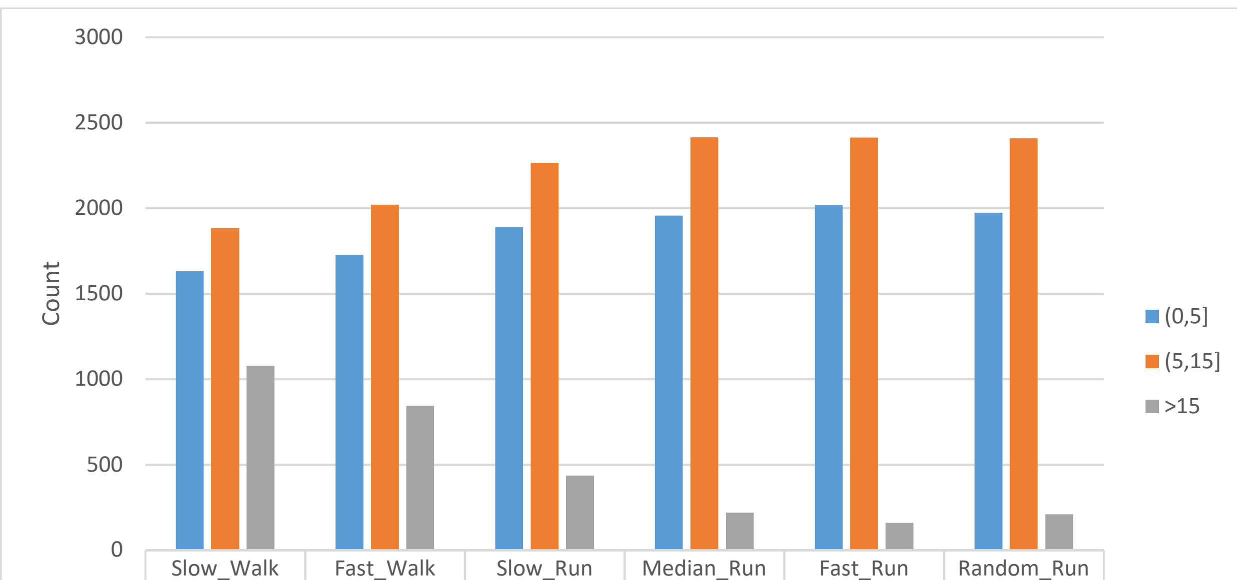
5.4.1. Reaction Time (Anisotropic + Reaction)

As mentioned in section 5-3, reaction times delay were calculated based on the different stated responses and supporting literature (Proulx & Fahy, 1997; Yuzal et al., 2015; Mas et al., 2012). Figure 5-20 and Figure 5-21 show the respective counts of agents and agent groups per speed category to reach safety for each time brackets. Similar to the night time scenario, the number of agents reaching the safe area in 15 minutes or less has lowered from 3,805 to 3,513 agents for slow walk scenario, a 7.67% decrease.



	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	592	630	701	726	750	734
(5,15]	564	591	659	727	736	744
>15	388	323	184	91	58	66

Figure 5-20 Anisotropic travel time + reaction delay output of the PEM for groups at different speed scenarios.

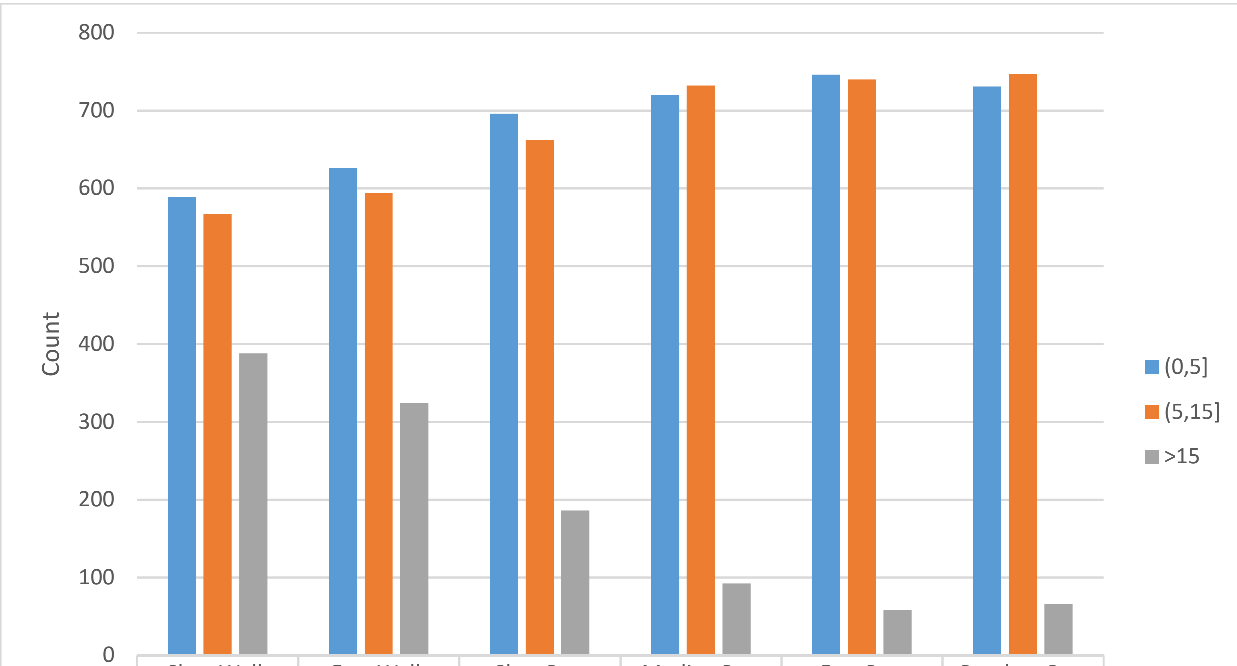


	Slow_Walk	Fast_Walk	Slow_Run	Median_Run	Fast_Run	Random_Run
(0,5]	1630	1726	1889	1956	2018	1973
(5,15]	1883	2020	2265	2415	2413	2408
>15	1077	844	436	219	159	209

Figure 5-21 Count of individuals to reach safety using anisotropic travel time and reaction delay at different speed scenarios.

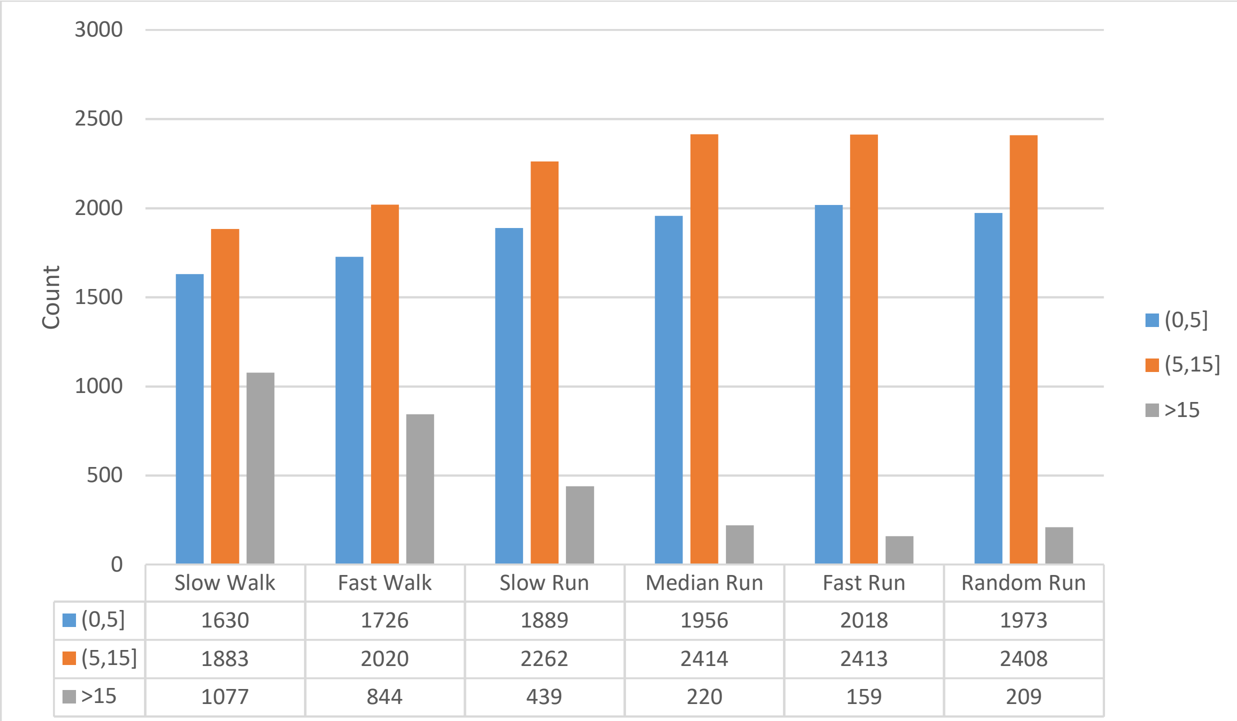
5.4.2. Evacuation Time (Anisotropic + Reaction + Fatigue)

Figure 5-22 and Figure 5-23 shows the respective counts of the created groups and agents that reached the safe area under the different speed scenarios. Similar to the night time scenario, there were very few instances where evacuation distance was 1,000 meters or more. Therefore, the number of agents reaching safety under $ATT + RT + FT$ is close to the number of agents under just $ATT + RT$. In fact, the fast run scenario, for instance, shows a difference of 155 agents between the ATT and TTT.



	Slow Walk	Fast Walk	Slow Run	Median Run	Fast Run	Random Run
(0,5]	589	626	696	720	746	731
(5,15]	567	594	662	732	740	747
>15	388	324	186	92	58	66

Figure 5-22 Count of groups to reach safety after considering fatigue and reaction time at different speed scenarios.



	Slow Walk	Fast Walk	Slow Run	Median Run	Fast Run	Random Run
(0,5]	1630	1726	1889	1956	2018	1973
(5,15]	1883	2020	2262	2414	2413	2408
>15	1077	844	439	220	159	209

Figure 5-23 Count of individuals to reach safety after considering fatigue and reaction time at different speed scenarios.

5.4.3. Population to Safety

Figure 5-24, Figure 5-25, Figure 5-26 show the respectively the ATT, RT, and FT of the day time scenario for the agents in the model. Similar to the night time scenario, these figures show the differences in the number of agents reaching safety for the different time penalties scenarios. For the slow walk scenario, a 13.8% decrease in the number of agents reaching the safe area can be observed from the anisotropic travel time to the anisotropic time pus reaction and fatigue delays.

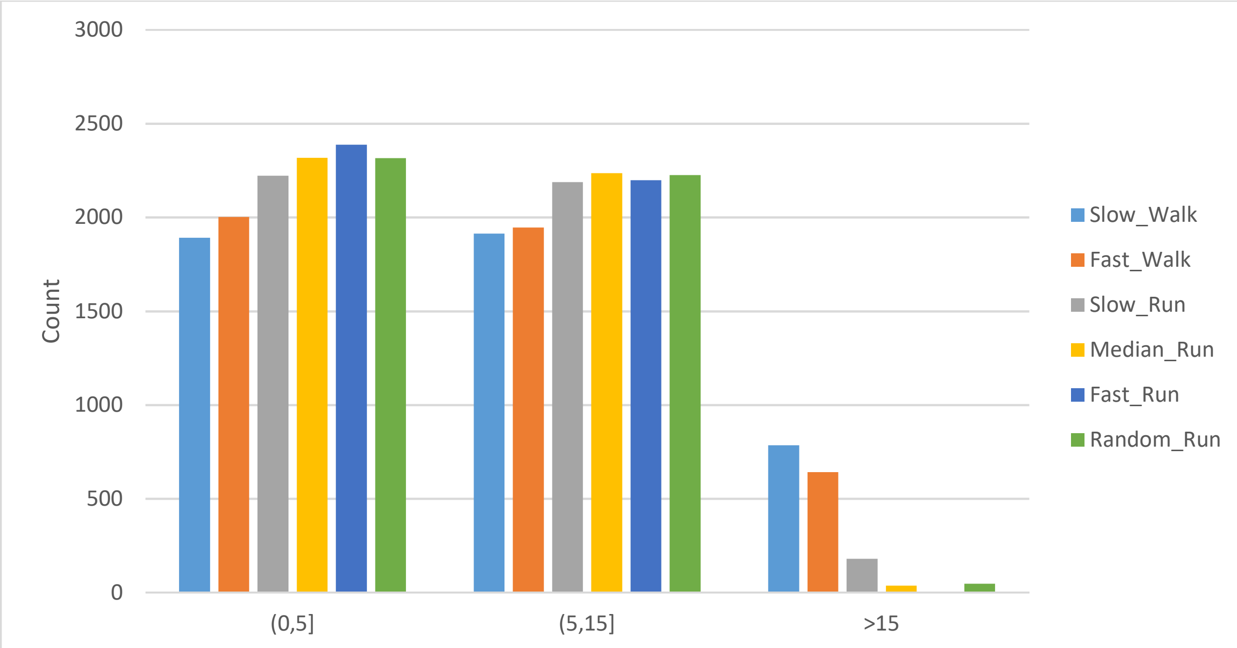


Figure 5-24 Count of individuals to reach safety using anisotropic travel time (ATT) at different speed scenarios.

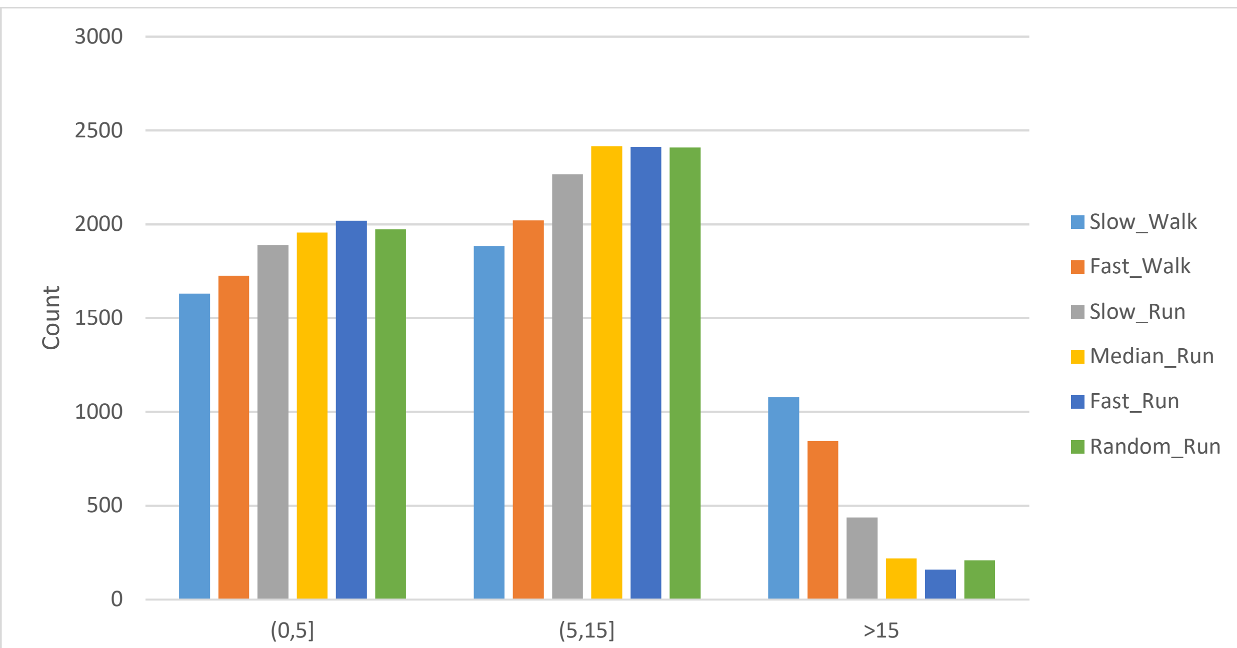


Figure 5-25 Count of individuals to reach safety using anisotropic travel time (ATT) and reaction time (RT) at different speed scenarios.

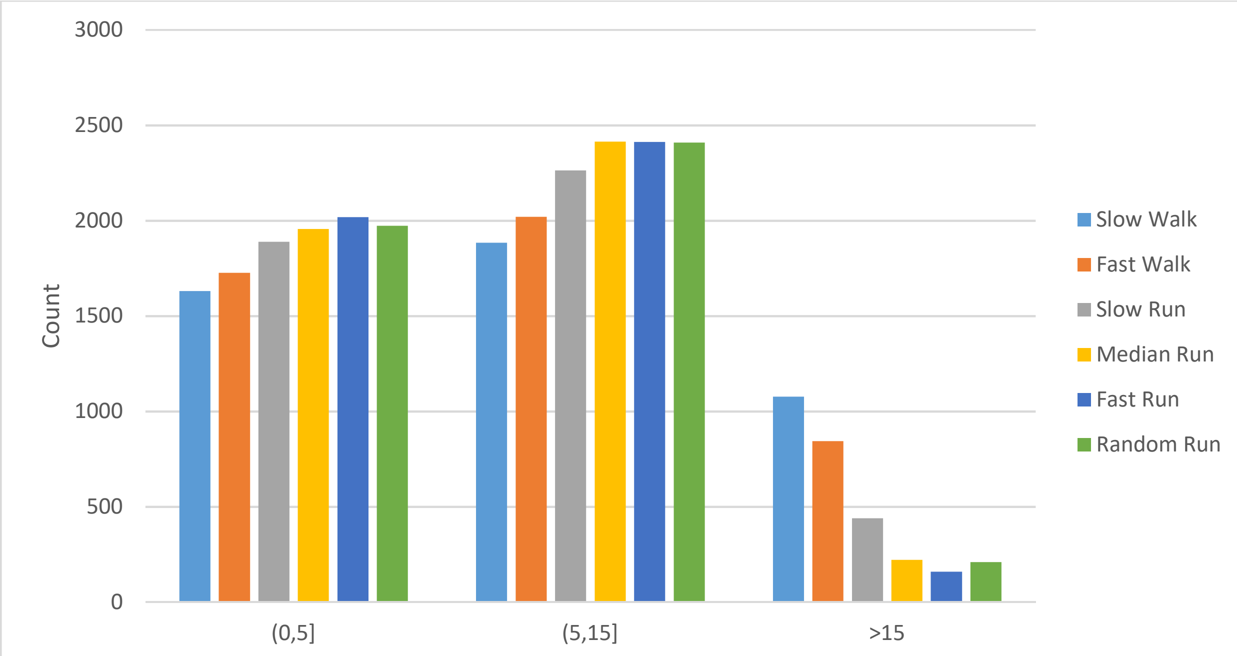


Figure 5-26 Count of individuals to reach safety after considering fatigue and reaction time at different speed scenarios.

One of this PEM objective is to provide different tools to evaluate pedestrian evacuation. The combination of the different evacuation speeds, the analysis of anisotropic, reaction, and fatigue time, and finally the results of a day and night time scenarios, combine to create multiple levels of information that can help understand the complexity of a real life pedestrian evacuation. Table 5-7 and Table 5-8 show the count of people to reach safety under the different time brackets for the respective night and day time scenarios. As expected, faster evacuation speeds show a considerable difference in the number of people for all the time brackets. Similarly, moving from anisotropic to penalties based on reaction time and fatigue reflect a decrease in the number of people to reach the safe zone. The data presented in these tables supports the idea that adding reaction and fatigue time will help estimating better the dynamics of population evacuation. When comparing the slow walk evacuation speed for the night time to the day time scenarios, the percentages of people reaching the safe area show a reduction equivalent to 9.56% and 13.8%, respectively.

Table 5-7 Number of people to reach the safe area under each time bracket and evacuation speed for the night time scenario.

	(0,5]			**(5,15]**			**>15**		
	ATT	**RT**	**FT**	**ATT**	**RT**	**FT**	**ATT**	**RT**	**FT**
Slow Walk	1758	1590	1590	2079	2057	2057	1065	1255	1255
Fast Walk	1834	1693	1693	2197	2235	2234	871	974	975
Slow Run	2078	1878	1878	2587	2607	2580	237	417	444
Median Run	2211	1948	1948	2675	2874	2865	16	80	89
Fast Run	2233	2005	2005	2665	2888	2886	4	9	11
Random Run	2066	1876	1876	2558	2686	2681	278	340	345

Table 5-8 Number of people to reach the safe area under each time bracket and evacuation speed for the day time scenario.

	(0,5]			**(5,15]**			**>15**		
	ATT	**RT**	**FT**	**ATT**	**RT**	**FT**	**ATT**	**RT**	**FT**
Slow Walk	1891	1630	1630	1914	1883	1883	785	1077	1077
Fast Walk	2002	1726	1726	1946	2020	2020	642	844	844
Slow Run	2222	1889	1889	2188	2265	2262	180	436	439
Median Run	2317	1956	1956	2236	2415	2414	37	219	220
Fast Run	2387	2018	2018	2199	2413	2413	4	159	159
Random Run	2316	1973	1973	2226	2408	2408	48	209	209

5.5 Sensitivity Analysis

Table 5-9 and Table 5-10 show some sub-county level descriptive statistics of the time in minutes it takes an agent to reach the safe area under the different for each of the evacuation speeds and the night, and day time scenarios. For the night time scenario, Calvache and Córcega presents the maximum travel time to the safe area of 29 and 19 minutes for the slow walk and fast run evacuation speed scenarios. When compared to the day time scenario, Calvache presents travel times of 42 and 19 minutes, whereas slow walk and fast run times travel times in Córcega are 43 and 27 minutes. Clearly, the travel times under the day scenario are higher than during the night. This difference can be attributed to the reaction times. For instance, during the night, agents that represent family structures does not have to travel for their dependents, whereas during the day, agents that are at work can experience higher reaction times by trying to pick up their dependents.

Table 5-9 Minimum, average, and maximum of the night time evacuation times for the different evacuation speeds of the total evacuation time ($\mathbf{ATT + RT + FT}$)

	Slow Walk			Fast Walk			Slow Run		
Sub-county	**min**	**mean**	**max**	**min**	**mean**	**max**	**min**	**mean**	**max**
Barrero	0	3	12	0	3	11	0	2	8
Rincón Pueblo	0	4	10	0	4	9	0	3	8
Calvache	0	18	29	0	16	25	0	13	21
Pueblo (Córcega)	0	12	29	0	11	25	0	9	21
Ensenada	0	6	14	0	5	13	0	4	11
Puntas	0	3	7	0	3	7	0	2	6
Río Grande	0	1	1	0	1	1	0	1	1
	Median Run			**Fast Run**			**Random Run**		
Sub-county	**min**	**mean**	**max**	**min**	**mean**	**max**	**min**	**mean**	**max**
Barrero	0	2	7	0	2	7	0	2	9
Rincón Pueblo	0	3	8	0	3	7	0	4	8
Calvache	0	12	19	0	11	19	0	13	27
Pueblo (Córcega)	0	9	19	0	8	19	0	9	27
Ensenada	0	4	10	0	4	10	0	4	12
Puntas	0	2	6	0	2	6	0	2	6
Río Grande	0	1	1	0	1	1	0	1	1

Table 5-10 Table with the minimum, average and max of the day scenario evacuation times for the different evacuation speeds of the total evacuation time ($\boldsymbol{ATT + RT + FT}$)

	Slow Walk			Fast Walk			Slow Run		
Sub-county	**min**	**mean**	**max**	**min**	**mean**	**max**	**min**	**mean**	**max**
Barrero	0	4	15	0	4	14	0	3	13
Rincón Pueblo	0	5	14	0	4	13	0	4	11
Calvache	1	15	42	1	13	39	0	11	32
Pueblo (Córcega)	0	12	43	0	11	39	0	9	31
Ensenada	0	6	34	0	6	31	0	5	22
Puntas	0	4	12	0	4	11	0	3	10
Río Grande	1	1	2	1	1	2	1	1	1
	Median Run			**Fast Run**			**Random Run**		
Sub-county	**min**	**mean**	**max**	**min**	**mean**	**max**	**min**	**mean**	**max**
Barrero	0	3	12	0	3	11	0	3	13
Rincón Pueblo	0	4	10	0	4	10	0	4	10
Calvache	0	10	32	0	9	32	0	10	32
Pueblo (Córcega)	0	8	28	0	8	27	0	8	27
Ensenada	0	5	20	0	4	20	0	5	20
Puntas	0	3	9	0	3	9	0	3	10
Río Grande	1	1	1	1	1	1	1	1	1

Finally, Table 5-11 and 5-12 show the percentage change in evacuation times in minutes and in number of people to reach safety when moving from slow speed to fast speed under different scenarios. This table shows the average amount of time that separates each of the evacuation speed scenario using equation:

$$Percentage\ change = \frac{(\bar{y}_{+} - \bar{y}_{-})}{\bar{y}_{-}}, \qquad (5\text{-}1)$$

Where $\bar{y}_{+} = new\ metric,$ and $\bar{y}_{-} = old\ metric.$

In Table 5-11 for instance, if one was to walk fast instead of slow, a reduction of 9.85% would be observed in their total travel time for the night time scenario, and a reduction of 2.70% for the day time scenario. Similarly, when comparing fast run to slow, travel times reduction of 40.79% and 11.05% for the night and day scenarios can be observed. The sharp differences for the night and day time scenarios are due to a variety of factors. Commercial buildings are closer to the safe area which indicates that employees have less distance to travel. During the night, agents travel mostly in groups and are constrained to the group slowest speed. On the other hand, agents during the day can evacuate individually, hence experiencing a higher evacuation speed. That translates into smaller percentage changes for the day scenario. Nonetheless, in an emergency evacuation, every second is crucial.

Table 5-11 Percentage change in evacuation times in minutes when moving from slow speed to fast speed under different scenarios.

	Night Scenario			**Day Scenario**		
	fast walk vs slow walk	**fast run vs slow run**	**fast run vs slow walk**	**fast walk vs slow walk**	**fast run vs slow run**	**fast run vs slow walk**
Barrero	-9.19%	-10.72%	-36.16%	-0.22%	-0.24%	-0.85%
Rincón Pueblo	-7.21%	-4.83%	-24.61%	-0.37%	-0.26%	-1.21%
Calvache	-9.85%	-18.32%	-40.79%	-2.70%	-3.76%	-11.05%
Pueblo (Córcega)	-8.46%	-12.06%	-32.34%	-1.86%	-2.13%	-6.76%
Ensenada	-7.41%	-6.60%	-26.02%	-2.89%	-3.07%	-10.29%
Puntas	-6.34%	-1.58%	-21.52%	-0.46%	-0.16%	-1.53%
Río Grande	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%
Grand Total	**-8.64%**	**-12.51%**	**-33.46%**	**-1.52%**	**-1.73%**	**-5.64%**

Calvache, in Table 5-12, shows an increase of 61% in the number of agents to reach the safe area if they were to run fast instead of walking slow for the night scenario in 5 minutes or less, whereas, the day scenario shows an increase of 333%, indicating that more than twice the people in the slow walk scenario would reach the safe area if they ran fast. As the evacuation speed increases, agents are able to reach the safe area faster. For instance, some agents that were in in the (5-15] minutes category are now in the [0-5] minutes category. This stresses the fact that faster evacuation speeds will yield better results in the number of people to reach safety and their travel times.

Table 5-12 Percentage change in number of people to reach safety when moving from slow speed to fast speed under different scenarios.

		Night			Day		
		fast walk vs slow walk	**fast run vs slow run**	**fast run vs slow walk**	**fast walk vs slow walk**	**fast run vs slow run**	**fast run vs slow walk**
(0-5]	**Barrero**	6%	6%	24%	6%	5%	18%
	Rincón Pueblo	6%	6%	23%	4%	4%	16%
	Calvache	0%	32%	61%	22%	63%	333%
	Pueblo (Córcega)	8%	9%	34%	11%	11%	47%
	Ensenada	8%	7%	29%	8%	8%	27%
	Puntas	3%	2%	11%	2%	2%	7%
	Río Grande	0%	0%	0%	0%	0%	0%
	Overall	**6%**	**7%**	**26%**	**6%**	**7%**	**24%**
(0-15]	**Barrero**	0%	0%	0%	0%	0%	0%
	Rincón Pueblo	0%	0%	0%	0%	0%	0%
	Calvache	23%	40%	117%	20%	45%	225%
	Pueblo (Córcega)	13%	9%	37%	14%	7%	41%
	Ensenada	0%	0%	0%	2%	3%	9%
	Puntas	0%	0%	0%	0%	0%	0%
	Rio Grande	0%	0%	0%	0%	0%	0%
	Grand Total	**7%**	**9%**	**28%**	**6%**	**7%**	**25%**

Figure 5-27 shows the empirical cumulative density function for the different speed scenarios. The percentages of agents reaching the safe area is clearly increasing when speed increase and, in general, at least 95% of the population in the hazard zone exit the TEZ in 25 minutes or less. This plot further shows that for a near-shore event whose tsunami waves hit the coast in 5 minutes or less, less than 50% of the population in the hazard zone will be able to reach safety. On the other hand, a local event whose tsunami waves hit the coast at least 15 minutes later allow for at least 75% of the population to evacuate the TEZ.

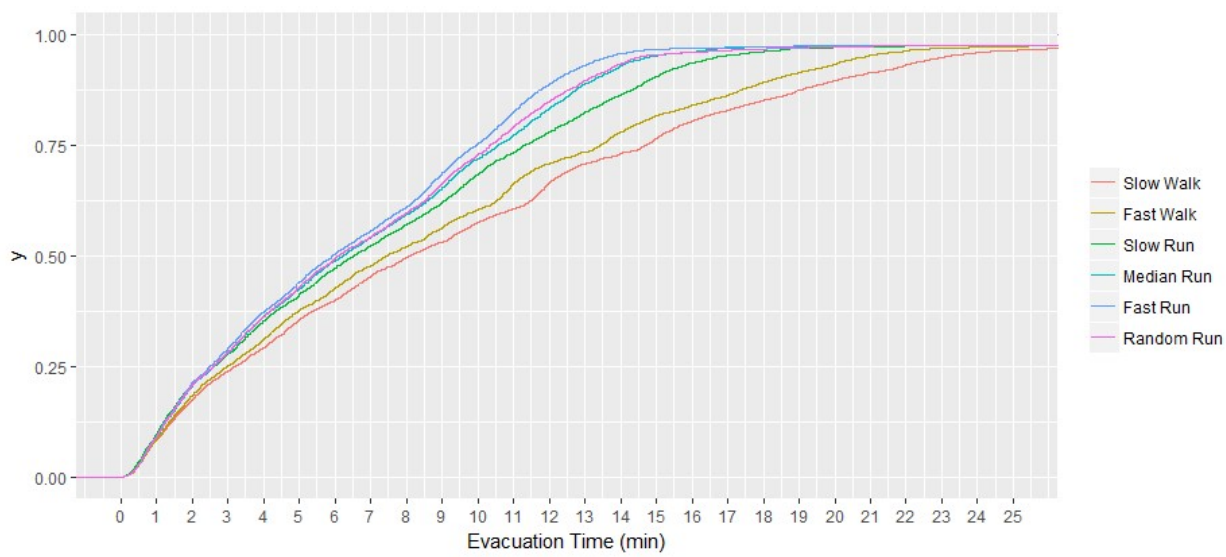


Figure 5-27 Empirical cumulative density function showing the percentage of agents to evacuate the TEZ up to 25 minutes travel time

Table 5-13 shows the time (in minutes) it takes a given proportion of the population to reach safety. For instance, 25% of the population, representing 1,148 agents, evacuate the TEZ in 3.19 minutes or less for the slow walk speed scenario and in 2.5 minutes or less for the fast run scenario.

Table 5-13 Upper bound for the time required for a given percentage of the population to reach safety.

Percentage of Population to Reach Safety	Count of Agents	Slow Walk	Fast Walk	Slow Run	Median Run	Fast Run	Random Run
5%	230	0.69	0.68	0.62	0.67	0.66	0.66
25%	1148	3.19	2.98	2.61	2.59	2.5	2.59
50%	2295	8.1	7.45	6.53	6.23	5.93	6.11
75%	3442	14.72	13.42	11.32	10.58	9.97	10.35
95%	4360	23.13	20.84	16.74	14.84	13.65	14.56

6 CHAPTER – CONCLUSIONS AND FUTURE WORK

Pedestrian evacuation models (PEMs) are used to simulate emergency evacuations and identify areas where the population is mostly at risk. There are many different approaches to create pedestrian evacuation models (PEM), each with its advantages and disadvantages. The microscopic approach provides a high level of detail, but requires extensive data processing. Because of the restrictions imposed on these models, they are usually custom-built for their study areas. This work showcased a custom tsunami PEM for the city of Rincón, Puerto Rico. Based on a mixed approach using anisotropic least cost distances and agent-based concepts, this PEM intends to relax many assumptions commonly found in similar work. The objectives are to improve population distribution, apply stated evacuation responses, impose a time penalty based on fatigue and reaction time, and use distinctive evacuation speeds based on attributes such as age and gender.

During an emergency evacuation, families are expected to travel together. To capture this reality, a custom model based on US Census and ACS data was created. This model assigns individuals to different geographical locations with the study area and uses the Census population count limits to create agent groups based on attributes such as age and gender. It must be noted that these groups were simulated, for the most part, to resemble family structures. That is, a female and male partner sharing one or more children.

Along with the concept that evacuation is done in groups, this PEM applies the slowest speed of each group agents to all the members of the corresponding group. This supports the theory that group travel time will be limited by the weakest link. Similarly, this PEM also penalizes total travel time with a reaction time delay. This time delay is estimated using a combination of the Rayleigh distribution and delay times based on a literature on evacuation for natural hazards. Still following the concept of the weakest link, the highest reaction time of an agent was attributed to all the members of its corresponding group. An additional penalty is also applied to the agents based on the distance they must travel to reach the safe areas as a proxy for fatigue. The minimum distance requirement to apply this fatigue penalty is 1,000 meters based on the work by Riegel (1981). Thus, using QGIS r.walk algorithm and a custom R script, this PEM calculates total evacuation time as a function of the anisotropic travel times, reaction time delays, and a fatigue penalty. While walking scenarios were considered in this work, the same running relative speed factor was used for all the agents for all the different evacuation speeds in the proposed PEM. Future work could improve upon these estimates by incorporating constants of relative speed that also target walking scenarios. Furthermore, this calculation could be improved if instead of being a constant of relative speed for either walking or running scenarios, the relative speed considered is not constant but, instead, dependent on an individual's set of attributes, such as each agent gender, age, and evacuation speed.

When analyzing the results of the PEM, the effects of reaction time delay and fatigue are clearly visible. For instance, the walking slow evacuation speed yielded an ATT count of 1,241 agents that took 15 minutes or more to reach the safe area. For the same time category, 1,464 agents reached the safe area when added reaction time delays, and 1,471 agents reached the safe area when added the fatigue penalty. It must be noted that since most of the stated evacuation responses were to evacuate immediately, the effect of the reaction delay was greatly controlled. On a similar note, the average travel distance is an estimated 650 meters, and only 25% of the structures fit the over the one-kilometer minimum requirement for the fatigue factor. This result in that close to 75% of the agents have similar evacuation speeds as $ATT + RT$.

As it stands now, this PEM can provide valuable insight to Rincón emergency response managers in order to estimate the number of people that can be affected by a tsunami, the at-risk areas, and help in the general mitigation against the potential arrival of tsunami waves. This PEM demonstrated that reaction time delays and fatigue time penalties can have a meaningful impact on the total travel time, hence the number of people to reach the safe area before the tsunami arrival. This model could be packaged into a tool to allow its application in municipalities other than Rincón. Lastly, a future recommendation for improving this work is to obtain a bigger sample of stated evacuation responses to better understand evacuation responses.

Validating the results of this model faces various difficulties. Since the results of this PEM are presented on three different levels: ATT, ATT+RT, and ATT+RT+FT, we will look at the validation possibilities for each level. The ATT results can be compared to other tools' results, such as the pedestrian evacuation analyst tool (Jones et al., 2014) or similar PEM that uses an anisotropic aspect. Walking travel times based on Google maps algorithm could also be used to compare pedestrian travel time. Google maps, nevertheless, presents some limitations, such as the evacuation speed cannot be changed, and evacuation is restricted to road networks.

The ATT+RT time in the proposed approach is customized on the combination of stated responses and delay times presented in the literature. The custom nature of this method makes it hard to find a comparative tool or method. The literature supports the notion that reaction times are based on complex decisions on an individual level. The reaction time delay presented in this work should be considered an estimation based on relevant factors. Since the stated responses and reaction time delays are inputs into the model, they can be modified and updated based on the user. A possible solution to validation would be to time an actual evacuation or a tsunami evacuation drill. Once a year, the Caribe Wave tsunami exercises provides an opportunity to time a pedestrian tsunami evacuation drill. These drills provide valuable awareness to the at-risk population but are limited in the fact that the fear element and the need for urgency are not present, people will not try to gather their dependents during an evacuation, and ample warnings remove the possible mean to measure reaction times.

The ATT+RT+FT faces similar difficulties as ATT+RT. Fatigue is not a factor that has been considered during evacuation to best of our knowledge. Therefore, there is not a model to compare the combination of the ATT, RT, and FT as it was presented in this model. Nonetheless, as explained previously, actual tsunami evacuation or tsunami evacuation drills for distances of 1,000 meters or more can be used to compare to the results of this PEM.

It is worth noting that, this PEM is not restricted to the use of road networks but access to open fields is permitted. During an evacuation drill, the evacuation routes often follow road networks and only apply the slow walk speed scenario.

APPENDIX I Custom Survey

University of Puerto Rico-Mayagüez
Department of Industrial Engineering
Flood Exposure and Sensitivity

ADAPTIVE CAPACITY TO FLOODS IN RINCÓN, PUERTO RICO

☐ *By checking this box, I confirm that I have read the informed consent form, I am 21 years or older, and I am willing to participate in this survey.*

1. Género: ☐ Masculino ☐ Femenino
2. Edad: ☐ 21-25 ☐ 26-30 ☐ 31-35 ☐ 36-40 ☐ 41-45
   ☐ 46-50 ☐ 51-55 ☐ 56-60 ☐ 61-64 ☐ 65+
3. Por favor marque su grado académico más alto:
   ☐ Menor de escuela superio ☐ Diploma de escuela superi ☐ Grado asociado
   ☐ Bachillerato ☐ Maestría ☐ Doctorado
4. Por favor, indique los idiomas en los que se puede comunicar con fluidez:
   ☐ Español ☐ Inglés ☐ Otro
5. ¿En qué ciudad reside?
   ☐ Rincón ☐ ________________, Puerto Rico ☐ Otro
6. ¿Se está hospedando en Rincón?
   ☐ Sí ☐ No
7. ¿En qué tipo de hospedaje?
   ☐ Residencia propia ☐ Residencia rentada ☐ Instalación recreativa ☐ Otro: ______________
8. Califique su familiaridad con la zona de Rincón.

No familiarizado	1	2	3	4	5	6	7	8	9	10	**Sumamente familiarizado**

9. ¿Mientras está en Rincón, en qué barrio pasa la mayoría de su tiempo?
   ☐ Atalaya ☐ Barrero ☐ Calvache ☐ Cruces ☐ Ensenada
   ☐ Jagüey ☐ Pueblo (Córcega) ☐ Puntas ☐ Rincón Pueblo ☐ Río Grande

   Comentarios:

   ____

10. Si pernocta en Rincón, por favor provea la siguiente información sobre las personas que viven/están viajando con usted.

Edades	<18	18-65	65+	**Discapacitados**	<18	18-65	65+	**Dependientes**	<18	18-65	65+
Total				**Total**				**Total**			

11. Califique cuán severamente ha sido afectado(a) por eventos de inundaciones en el pasado.

No afectado 1 2 3 4 5 6 7 8 9 10 **Extremadamente afectado**

12. Califique cuán severamente conocidos han sido afectados por eventos de inundaciones en el pasado.

No afectado 1 2 3 4 5 6 7 8 9 10 **Extremadamente afectado**

13. Califique cuán severamente podría verse afectado(a) por una inundación.

No afectado 1 2 3 4 5 6 7 8 9 10 **Extremadamente afectado**

14. La inundación más reciente en Rincón fue el resultado de una vaguada en el 2003. Califique cuán probable sería verse afectado por una inundación durante el transcurso de su vida.

Poco Probable 1 2 3 4 5 6 7 8 9 10 **Extremadamente probable**

15. Califique cuán severamente podría verse afectado(a) por un tsunami.

No afectado 1 2 3 4 5 6 7 8 9 10 **Extremadamente afectado**

16. El último tsunami en afectar a Rincón ocurrió en el 1918. Califique cuán probable sería verse afectado por un tsunami durante el transcurso de su vida.

Poco probable 1 2 3 4 5 6 7 8 9 10 **Extremadamente probable**

17. Califique su percepción sobre la efectividad de los sistemas de alerta de Rincón. ☐ N/A

No efectiva 1 2 3 4 5 6 7 8 9 10 **Extremadamente efectiva**

18. Califique su nivel de preparación para un evento de inundación.

Muy pobre 1 2 3 4 5 6 7 8 9 10 **Excelente**

19. ¿Conoce la localización de los puntos de asamblea de Rincón? ☐ Sí ☐ No

20. ¿Conoce otros lugares en Rincón que serían consideradas zonas seguras en el caso de una inundación o tsunami? ☐ Sí ☐ No

21. ¿Qué medidas ha tomado en preparación para un evento de inundación? Marque TODAS las que apliquen.
- ☐ Obtuve información sobre cómo protegerme ante el embate de una inundación. Fuente:___________
- ☐ Desarrollé un plan de desalojo para mi hogar
- ☐ Preparé un bulto con posesiones importantes (p.ej., documentos importantes, medicamentos)
- ☐ Realicé cambios estructurales en la propiedad
- ☐ Compré suministros de emergencia (p.ej., planta eléctrica, cisterna, comida)
- ☐ Instalé un sistema de alerta en el hogar (p.ej., radio NOAA)
- ☐ Ninguna
- ☐ Otro:____
_

22. Califique su nivel de entendimiento de las señales de peligro ante la potencial amenaza de una inundación o tsunami.

Muy Pobre 1 2 3 4 5 6 7 8 9 10 **Excelente**

23. ¿Cuáles de los siguientes reconoce como una señal significativa de una amenaza por inundación o tsunami? Marque TODAS las que apliquen.
- ☐ Lluvia de larga duración o alta intensidad
- ☐ Rotura de un embalse o represa
- ☐ Liberación repentina de agua aguantada por escombros
- ☐ Temblor que dure más de un minuto
- ☐ Temblor fuerte
- ☐ Cambio repentino en el nivel del mar
- ☐ Rugido fuerte proveniente del mar
- ☐ Comportamiento animal inusual
- ☐ Otro:____

24. De experimentar una señal de alerta de inundación, ¿cómo respondería? ¿Reaccionaría diferente si se encuentra separado de alguna población dependiente?
____
____
____

- ☐ No haría nada.
- ☐ Buscaría asistencia para desalojar.
- ☐ Desalojaría inmediatamente.
- ☐ Solo si soy forzado(a) por las autoridades.

- [ ] Ayudaría a otros y luego desalojaría.
- [ ] Reuniría todos mis dependientes y luego desalojaría.
- [ ] Esperaría por una notificación oficial (p.ej., sirena, RSPR, TV, radio). Fuente:____________________
- [ ] Otro
- [ ] Pánico y luego desalojaría.
- [ ] Pánico y buscaría asistencia.
- [ ] Contactaría mis dependientes y luego desalojaría.

¿Cambiaría respuesta con población dependiente? ☐ Sí ☐ No ☐ N/A

25. De experimentar una señal de alerta de tsunami, ¿cómo respondería? ¿Reaccionaría diferente si se encuentra separado de alguna población dependiente?
____
____
____

- [ ] No haría nada.
- [ ] Buscaría asistencia para desalojar.
- [ ] Ayudaría a otros y luego desalojaría.
- [ ] Reuniría todos mis dependientes y luego desalojaría.
- [ ] Esperaría por una notificación oficial (p.ej., sirena, RSPR, TV, radio). Fuente:____________________
- [ ] Otro
- [ ] Desalojaría inmediatamente.
- [ ] Solo si soy forzado(a) por las autoridades.
- [ ] Pánico y luego desalojaría.
- [ ] Pánico y buscaría asistencia.
- [ ] Contactaría mis dependientes y luego desalojaría.

¿Cambiaría respuesta con población dependiente? ☐ Sí ☐ No ☐ N/A

26. De desalojar, ¿lo haría a pie o en carro? Marque TODAS las que apliquen.
☐ A pie ☐ Carro ☐ Otro:________________

27. Si desaloja como peatón, ¿cuáles de las siguientes haría?
☐ Caminar ☐ Correr ☐ Combinación de ambos ☐ N/A

28. Califique su condición física.

Muy pobre 1 2 3 4 5 6 7 8 9 10 **Excelente**

29. ¿Cuáles de las siguientes lo harían moverse más rápido durante un desalojo? Marque TODAS las que apliquen.
- [ ] Ver el agua acercándose
- [ ] Escuchar un sistema de alerta del gobierno siendo activado
- [ ] Ver otras personas desalojando Cantidad mínima: ________
- [ ] Otro:____

30. ¿Cuáles de las siguientes le harían moverse más lento durante un desalojo? Marque TODAS las que apliquen.

- [ ] Multitudes
- [ ] Discapacidades
- [ ] Fatiga
- [ ] Población dependiente
- [ ] Otro:___________________________

31. Califique su habilidad para recuperarse de los daños ocasionados por una inundación.

Pobre	1	2	3	4	5	6	7	8	9	10	**Excelente**

32. Califique cuán accesible sería obtener ayuda gubernamental para recuperarse de los daños ocasionados por un desastre natural. - [ ] N/A

No accesible	1	2	3	4	5	6	7	8	9	10	**Extremadamente accesible**

33. ¿Cómo obtendría los recursos económicos para recuperarse de los daños asociados a un desastre natural? Marque TODAS las que apliquen.

- [ ] Dependería de mis ahorros personales.
- [ ] Dependería de préstamos personales.
- [ ] Dependería de ayuda de mis familiares y amistades.
- [ ] Dependería de ayuda gubernamental (p.ej., FEMA).
- [ ] Me encargaría personalmente de la mayoría de las reparaciones.
- [ ] Otro: ____

34. Indique su estatus laboral actual:

- [ ] Empleado
- [ ] Desempleado
- [ ] Retirado
- [ ] Estudiante
- [ ] Discapacitado

35. ¿Cuál es el ingreso anual de su hogar?

- [ ] <$15,000
- [ ] $15,000 – 25,000
- [ ] $25,000 – 75,000
- [ ] $75,000+

Cuestionario conducido por: ________________________________ Fecha: _______________-

Appendix II Survey guesthouse in Rincón, PR

University of Puerto Rico-Mayagüez
Department of Industrial Engineering
Exposition and Sensitivity to Inundation

QUESTIONAIRE FOR GUESTHOUSES IN RINCÓN, PR

1. Name of the guesthouse: ______________________________

2. Type of guesthouse: ☐ Private ☐Public

☐ Hotel ☐ Touristic Villas ☐ Guest House ☐ Hostel
☐ Eco Guest House ☐ Bed & Breakfast ☐ Agro Guest House

3. ¿ What months you considered the season peak of your guesthouse?

☐ January ☐ April ☐ July ☐ October
☐ Fenruary ☐ May ☐ August ☐ November
☐ March ☐ June ☐ September ☐ December

General public service

a) ______________________ Frequency: __________ Capacity: __________
b) ______________________ Frequency: __________ Capacity: __________
c) ______________________ Frequency: __________ Capacity: __________
d) ______________________ Frequency: __________ Capacity: __________

4. [Optional] Number of employees: __________

☐ 0-10 ☐ 11-25 ☐ 26-50 ☐ 51-100 ☐ 101-250 ☐ 251-350 ☐ 351-500

Infrastructure

5. Total room: ____________________

Double: _______ Capacity: _______ Single: _______ Capacity: _______
Others: ______________________________ Capacity: _______
Others: ______________________________ Capacity: _______
Comments: ____

6. Monthly occupation percentage:

January: ________ April: ________ July: ________ October: ________
Fenruary: ________ May: ________ August: ________ November: ________
March: ________ June: ________ September: ________ December: ________

7. [Optional] Average guest occupance per year: ________

COMMENTS:____

Survey conducted by: ______________________________ **Date:** ____________________

Appendix III IRB approval

Comité para la Protección de los Seres Humanos en la Investigación
CPSHI/IRB 00002053
Universidad de Puerto Rico – Recinto Universitario de Mayagüez
Decanato de Asuntos Académicos
Call Box 9000
Mayagüez, PR 00681-9000

12 de octubre de 2013

Dra. Saylisse Dávila Padilla
Sr. Juan G. Ayala Reyes
Depto. de Ingeniería Industrial
Call Box 9000
Recinto Universitario de Mayagüez
Universidad de Puerto Rico
Mayagüez, Puerto Rico 00681-9000

Estimada Dra. Dávila Padilla y Sr. Ayala Reyes:

La presente es para comunicarle formalmente que el Comité para la Protección de los Seres Humanos en la Investigación (CPSHI) ha determinado que su proyecto de investigación, titulado *A Hierarchical Assessment of the Vulnerability of Tsunamis of Puerto Rican Coastal Communities,* no involucra a sujetos humanos, según la definición que aparece en 45 CFR 46.102(f).

Agradecemos su compromiso con los más altos estándares de protección de los seres humanos y le deseamos éxito en su proyecto. Queda de usted,

Atentamente,

Rosa F. Martínez Cruzado

Rosa F. Martínez Cruzado, Ph.D.
Presidente
CPSHI/IRB
UPR - RUM

Teléfono: (787) 832 - 4040 x 6277, 3807, 3808 – **Fax:** (787) 831-2085 – **Página Web:** www.uprm.edu/cpshi
Email: cpshi@uprm.edu

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