Natural Hazards Review

An Agent-Based Modeling Approach to Protective Action Decision-Related Travel During Tornado Warnings

--Manuscript Draft--

Manuscript Number:	NHENG-1783R1
Full Title:	An Agent-Based Modeling Approach to Protective Action Decision-Related Travel During Tornado Warnings
Manuscript Region of Origin:	UNITED STATES
Article Type:	Technical Paper
Section/Category:	Engineering
Manuscript Classifications:	Disaster warning systems; Hurricanes, tornadoes, and cyclones; Natural disasters; Simulation and modeling
Funding Information:	National Oceanic and Atmospheric Administration (NA16OAR4320115) — Joshua J. Hatzis
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Question	**Response**
The journal requires that all submissions fall within its aims and scope, explained here. Please explain how your submission fits the journal's aims and scope.	We believe that this manuscript is appropriate for publication by Natural Hazards Review because it contains original research related to a natural hazard (tornadoes) and its interaction with society through tornado warning response. The focus on travel behavior is also relevant from a civil engineering perspective. This research also has

An Agent-Based Modeling Approach to Protective Action Decision-Related Travel During Tornado Warnings

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Abstract

Tornadoes represent a significant threat to life and property and tend to evoke protective action in most people. Studies have suggested that many people travel to the nearest storm shelter or flee the area, rather than sheltering-in-place as recommended by the National Weather Service. While shelter-in-place is the recommendation of the National Weather Service, for tornado safety, few studies have quantified the risk reduction when compared to traveling to a storm shelter or fleeing the area. To address this knowledge gap, we developed an agent-based model, the Tornado Warning-Induced Shelter, Travel, and Evacuation Response Agent-Based Model (TWISTER ABM), to simulate protective action behaviors in the city of Norman, Oklahoma under eight protective action scenarios including: (1) everyone who responds to the warning (responders) seeks refuge in the nearest sturdy building (seek refuge), seeks shelter in a FEMA-rated shelter (seek shelter), or flees the area, (2) all responders flee the area, (3), all responders seek refuge (shelter-in-place), (4) all responders seek shelter, (5) all agents flee the area, (6) all agents seek refuge, (7) all agents seek shelter, (8) all agents do nothing. We found that, for an EF5 tornado hitting Norman at rush hour, the overall fatality rates by protective action type were 0.6% for those who took no action, 0.3% for those who sought refuge, 1.5% for those who sought shelter, and 1.1% for those fleeing the area. We also found that fatality rates were reduced by a factor of 6.6 for scenario 6 (shelter-in-place) over scenario 7 (travel to a FEMA-rated shelter). We believe that models such as TWISTER ABM can be used by the NWS and Emergency Managers in their attempts at communicating the effectiveness of shelter-in-place.

Keywords: Agent-based modeling, tornado warning and response, travel, GIS

Practical Applications

Tornadoes are dangerous windstorms that can cause serious injury or death to people who do not take protective action. The National Weather Service states that sheltering-in-place is the safest form of protective action, but no studies to date have shown how much it can reduce casualties. We developed an agent-based model to study how changes in protective action type can influence the fatality rate (fatalities per 1,000 residents) caused by a tornado in the city of Norman, Oklahoma. We found that, for an EF5 tornado hitting Norman at rush hour, the overall fatality rates, for all model runs, were lowest for agents who sheltered-in-place (0.3%) and highest for those who traveled to public shelters (1.53%). We also found that fatality rates were lowest when all agents sheltered-in-place (0.24%) and highest when every agent responding to the warning traveled to public shelters (1.54%), a 6.6x reduction for shelter-in-place. We believe that models such as TWISTER ABM can be used by the NWS and Emergency Managers in their attempts at communicating the effectiveness of shelter-in-place.

Introduction

Tornadoes are violent storms with wind speeds potentially exceeding 320 km/h. Tornadoes are capable destroying even sturdy buildings, crumpling mobile homes, flipping cars and trucks, and lofting people into the air (Edwards 2021). As a result of the extreme danger posed by tornadoes, the National Weather Service (NWS), Federal Emergency Management Agency (FEMA), and the American Red Cross all recommend taking immediate protective action in the event of a tornado warning. The primary recommendation is to shelter-in-place (in an interior room on the lowest level of the building or in a specially constructed storm shelter), if inside a sturdy building, or to drive to the nearest sturdy building, if outside, in a vehicle, or in a mobile home as even weak tornadoes can potentially be deadly in those circumstances (Schmidlin 1997; Schmidlin et al. 2002; Farley 2007; Edwards 2021).

Longer distance travel, such as to flee the area or travel to a non-local public shelter, is generally not recommended as vehicles can be dangerous during tornadoes. While the number of motor vehicle fatalities in tornadoes in the US is low (8-9% according to studies by Paulikas and Schmidlin (2017) and Fricker and Friesenhahn (2022)), vehicles provide little protection against tornado-strength winds or large debris. Wind speeds as low as 139 km/h may roll or loft vehicles (Paulikas et al. 2016; Paulikas and Schmidlin 2017), falling debris can crush vehicles (Schmidlin 2009) and wind-launched projectiles can pierce vehicles causing injury or death (Blair and Lunde 2010). Vehicles can and have been safely used to flee from tornadoes (Carter et al. 1989; Duclos and Ing 1989; Daley et al. 2005); however, tornadoes can suddenly change direction (Nixon and Allen 2021), their full circulation is not always visible (Wurman et al. 2014), and debris can be launched from significant distances (Snow et al. 1995; Black et al. 2019) making it difficult to know one is in a safe position relative to the tornado. In addition, travel on limited access roads (e.g., interstates) can prevent immediate escape from an approaching tornado (Blair and Lunde 2010), and heavy traffic can result in slow movement or grid-locked roads potentially placing hundreds of vehicles in harm's way (Garfield and Smith 2014; Hatzis and Klockow-McClain 2022).

Despite the NWS recommendations, many people take to the roads to drive to public shelters or evacuate. A study by Hammer and Schmidlin (2002) on responses to the May 3, 1999 Oklahoma City tornado found that 21% of the respondents reported driving to a shelter, someone else's home or to somewhere outside the at risk area. Another study by Sherman-Morris (2010) of university student responses to a 2008 tornado warning in Mississippi found that 11.1% of students reported driving somewhere else after the warning was issued. A number of behavioral intent surveys have had similar findings, although these are not always indicative of actual responses (Sorensen 2000). Among surveyed residents of Calgary, Canada, Durage et al. (2014) found that 16.6% of those at home said they would leave the home in search of a neighborhood shelter or to flee the area, while 58% of those on the road said they would flee the area. A similar survey of residents of Austin, Texas by Schultz et al. (2010) found that among those at home 18% said they would leave home to get out of the tornado's path while 39% of those driving said they would stay in the car and drive away from the tornado. A final nationwide survey by Ripberger et al. (2015), found that while the intended response rate to tornado warnings increased as tornado intensity increased (77% (EF0) to 95% (EF5)) so to did the likelihood that people intended to leave home to find a shelter or flee the area in response (11% (EF0) to 39% (EF5)).

While shelter-in-place is the recommendation of the NWS, for tornado safety, it is unclear exactly how much it reduces tornado risk relative to travelling to a local storm shelter or fleeing the area. One way to assess this difference is through the simulation of protective action behaviors and hazard impacts. Evacuation modelling has been used to simulate evacuations in response to many types of hazards including tsunamis, hurricanes, wildfires, and chemical spills (Chen et al. 2006; Beloglazov et al. 2016; Wang et al. 2016; Watts 2018). In such models, evacuees travel via pedestrian or road networks from their position at outset of the hazard to some safe location, either in a building or out of the at-risk area. These models rely on detailed transportation networks and are used to determine variables such as (1) the evacuation clearance time for an evacuation (Zockaie et al. 2014; Wang et al. 2016; Kimms and Maiwald 2018), (2) the influence of mitigation efforts, such as staged (phased) evacuations (Zhang et al. 2014), and contraflow (Wolshon 2001), on evacuation clearance time, (3) as well as potential casualties among evacuees who are unable to complete their trip in time (Wang et al. 2016).

To assess the question of the effectiveness of the shelter-in-place paradigm, we have developed one such agent-based modeling framework for studying protective action behaviors in response to tornado warnings. We use this model to perform a case study of a violent tornado hitting a community within the city of Norman, Oklahoma, during rush hour, to show how the shelter-in-place paradigm reduces both fatalities, and the time require to take protective action, when compared to other safety paradigms (e.g., evacuation or travel to storm shelters that are Federal Emergency Management Agency (FEMA) rated to withstand EF5 level winds).

Development of tornado warning-induced shelter, travel and evacuation response agent-based model (TWISTER ABM)

The Tornado Warning-Induced Shelter, Travel, and Evacuation Response Agent-Based Model (TWISTER ABM) was designed as a modification to the Agent-Based Tsunami Evacuation Model (ABTEM) by Wang et al. (2016). ABTEM was designed in the NetLogo Agent-Based Modeling (ABM) platform (Wilensky 1999), a free open-source software that has an easy to learn programming language and is on its way to becoming a standard tool in the development of ABMs (Thiele et al. 2012). NetLogo allows users to simulate multiple agent types at once and define many parameters that can be explored to identify emergent phenomenon and enables them to visualize these phenomena over time (Railsback et al. 2006). NetLogo is well suited to community-scale evacuation modeling due to its ability to ingest GIS data and to study agent interactions which can lead to emergent behavior (Pan et al. 2007; Wang et al. 2016). In the ABTEM, Wang et al. (2016) simulate an evacuation of the city of Seaside, Oregon from a near-field tsunami caused by an earthquake on the Cascadia Subduction Zone. The agents choose to evacuate, either on foot or by car, to a horizontal or vertical tsunami shelter. A number of parameters control the agents' speeds as well as the percentage choosing to evacuate on foot or by car and the evacuation wait time. All travel in the model is by the road network with all roads considered one-way with one lane and a constant speed limit of 55 km/h. Following Wang et al (2016) we assume the roads remain clear throughout the evacuation and that there are no accidents. Travel by car is governed by the General Motors (GM) car-following model (Chandler et al. 1958; Herman et al. 1959). We set the model parameters as in Mostafizi et al (2017) to account for the reduced perception-reaction time (due to alertness) and increased acceleration and deceleration rates common during an emergency. The ABTEM has been used to study how fatalities vary by dominant evacuation mode (on foot or by car) (Mostafizi 2016; Wang et al. 2016), the effectiveness of vertical tsunami evacuations (Mostafizi et al. 2018, 2019) and unplanned network disruptions due to a tsunami (Mostafizi 2016; Mostafizi et al. 2017).

In the TWISTER ABM we consider how agents (hereafter, all references to agents will refer to all simulated persons within the model) travel and shelter or evacuate in response to a tornado warning. To do this, we performed extensive modifications to the ABTEM, including to the hazard, decision-making and fatality models. We also significantly modified the population distribution to represent the daily migration between home, work, play and errands and added background traffic to represent the impact of time of day on travel times. Like the ABTEM, TWISTER ABM has many parameters that can be controlled to test differences in fatality rate (per 1000 persons) or evacuation times due to factors such as the time of day, the amount of lead time before the tornado hits, the magnitude, width and speed of the tornado, and the number of available Federal Emergency Management Agency (FEMA) rated shelters (shelters that can withstand even the strongest tornadoes with winds exceeding 321.9 km/h (those rated five on the Enhanced Fujita (EF) scale)) (McDonald and Mehta 2006; FEMA 2021). Fig. ***1*** shows a screenshot of the NetLogo simulation environment. In Fig. 1, grey shading represents the damage path of the tornado with darker color cells experiencing higher wind speeds with a black tornado icon representing the current position of the center of the tornado, small squares represent buildings that are not FEMA-rated shelters (called refuges hereafter), large squares represent FEMA-rated shelters (called shelters hereafter), stars represent evacuation points, small x’s represent residents who have been killed by the tornado, flags represent residents who have successfully evacuated, dots represent residents who are taking no action, circles represent residents who are monitoring the situation, small triangles represent residents who are travelling to refuge, large triangles represent residents who are traveling to shelter, and arrow heads represent residents who are evacuating.

In the current version of the model, we assume that roads impacted by the tornado are navigable; however, it is entirely possible that sections of the road could be damaged by the tornado or covered in debris making them impassable (Bohonos and Hogan 1999). Like ABTEM, TWISTER ABM does have a functionality to break road network links to simulate network disruptions and this may be explored in future studies. As in ABTEM, all resident agents are assumed to be autonomous and heterogenous with respect to their characteristics. All agent choices are influenced by internal characteristics (*e.g.*, age, race) and the environmental cues (e.g., seeing or hearing the tornado) and their movement is influenced by agent interactions along the road network. Agent demographics are based on the American Community Survey (ACS) from the U.S. Census Bureau for the city of Norman. Oklahoma in 2019 (https://data.census.gov). Agents' decisions can change throughout the simulation; however, agents who choose to take protective action (seek protection in the nearest available sturdy building (i.e., not a mobile home) (seek refuge), seek protection in the nearest available building that is a FEMA-rated shelter (seek shelter), or flee the area (evacuate)) rarely change their decisions. The agents' ability to make protective action decisions during a tornado warning is based on responses from the Severe Weather and Society (WX Survey), a survey issued since 2017 where a representative sample of U.S. adults are asked recurring questions regarding forecast and warning reception, comprehension, and response, as well as one-time questions about important climate or weather topics such as weather impacts and severe weather climatology (Ripberger et al. 2019) (see Appendix 2 for more details). See Table 1 for a listing of key variables for agents. The primary outputs of the model are the fatality count, duration and distance of trips to refuges, shelters, and evacuation points, and the time required to reach the protective action destination. We chose to focus on fatalities over other injuries as this was the focus of the ABTEM (Wang et al. 2016; Mostafizi et al. 2017). Each model run begins with the setup of the model world and the issuance of a tornado warning, agents then proceed to make a decision regarding the type of protective action they take (if any) and then move towards their chosen destination. The model run ends with the dissipation of the tornado (see Fig. 2).

Study area and hazard scenario

This study takes place in the city of Norman in central Oklahoma. Norman is a city with an area of 463 km^2 and an estimated 2019 population of 124,880. The population of Norman is predominantly white (77.8%), non-Hispanic (91.5%) and in the middle class (median household income around $58,000) (U.S. Census Bureau 2019). We chose 2019 as the sample year for demographic information as if falls within the available years of weather survey data (2017-2021) (Ripberger et al. 2020a, b, c, d, 2021). Norman is in an area of high risk for tornadoes (Gensini and Brooks 2018; Moore and DeBoer 2019), including violent (EF4-5) tornadoes (Doswell et al. 2012; Hatzis et al. 2019) so it was well suited for this study. According to the National Weather Service (NWS), it has been directly impacted by tornadoes 31 times since 1890, including three EF4 tornadoes in 2010 and 2019 (NWS 2020a). The neighboring city of Moore has been impacted 23 times since 1890, including two EF5 tornadoes in 1999 and 2013 (NWS 2020b) that impacted populated areas causing many fatalities (Brooks and Doswell 2002; Burgess et al. 2014). Due to computational constraints, we restricted our study area to a 32.1 km^2 area in western Norman surrounding the I-35 corridor (see

Fig. ***3***).

The deadliest tornado to hit the Oklahoma City metropolitan area occurred in the early evening of May 3, 1999. On this day, a 1.6 km wide EF5 tornado (with Doppler measured wind speeds of 484.4 km/h (Edwards 2021)) tracked 59.5 km across the Oklahoma City area causing 36 direct fatalities in the communities of Bridge Creek, Newcastle, Oklahoma City, Moore, Del City, and Midwest City (NWS 1999; Speheger et al. 2002). Since this tornado passed within 2.7 km of Norman, it could have easily impacted the city (NWS 1999). In this study we imagine a case where a tornado of the same width (1.6 km), magnitude (EF5), and ground speed (45.1 km/h) as the May 3, 1999 Oklahoma City tornado, hits western Norman during rush hour (1700).

Monte Carlo simulation

Many components of TWISTER ABM are stochastic in nature to account for uncertainties in the way people make protective action decisions during tornado warnings, the actual location of people throughout the city at a given hour, and the location of storm shelters (the locations of homes with personal storm shelters is unknown and there are no official public shelters within the city of Norman). To capture this stochasticity, we conduct a series of 20 Monte Carlo simulations for each experiment (see Appendix 1 for the justification of using 20 simulations) using the Behavior Space module in NetLogo (Wilensky 1999).

Model components

The model requires many data sets including building points (centroids of buildings including data about the maximum EF level wind the building can withstand and the municipal zone the building falls within), terminal network points (points along the road network beyond which the agent will be considered safely evacuated), road network, park land (polygons representing municipal parks), agent demographics, EF wind field (percentage of a tornado's area experiencing winds at each EF level), milling time (waiting time before an agent makes a decision), road usage (frequency with which each road type (e.g., interstate, arterial) is used), mean tornado width, hourly probability of location, probability of tornado warning reception, comprehension, and response, probability of taking protective action. The derivation of each of these data sets is described in the Supplemental Information. The model itself consists of five submodels: population distribution, travel and background traffic, decision-making and protective action, fatality, and tornado hazard which are described below. See Appendix 2 for more details on the data sets used by the model.

Population distribution and normal movement

The number of people located in a community varies throughout the day, week, and seasons as people travel to work, visit friends, spend time outdoors, take vacations, run errands, etc. To take into account these daily migration patterns, the initial locations of the agents are based on the simulated time of day and the typical daily movement patterns of residents of the southern and midwestern U.S. according to the American Time Use Survey (ATUS). Agents are assigned an initial location at random based on where the ATUS results say people are located (e.g., at work, home, etc.) (see full details in Appendix 3).

Agents are also assigned a secondary location that the agent will head towards at a random model time step (between 0 and 3600) if they do not decide to take protective action first. The secondary location is similarly selected via a weighted random draw only it is based on the ATUS probabilities for the hour *following* the simulation. If the agent's initial location is on the road they will immediately head towards the secondary location, otherwise they will remain stationary until either the random time step is reached, or the agent decides to take protective action.

According to the 2020 U.S. census, the adult population (18 years of age and older) of the study area is 23,111 persons. However, due to computational constraints of NetLogo, with respect to agent-to-agent interactions, we have chosen to limit the number of agents simulated to 4000 (see Appendix 4 for more details on the justification for limiting the number agents to 4000).

Travel and background traffic

Travel in the TWISTER ABM is very similar to that described by the original agent-based tsunami evacuation model (Wang et al. 2016). Agents mostly travel by car along a simplified road network as they move from building to building or towards an evacuation point (one of the terminal network points) (see full details regarding road network travel in Appendix 5).

While most travel occurs via car along the road network agents must travel on foot between buildings or outdoor points and the road network. Additionally, travel was on foot if the destination was closer on foot than via the road network. Travel was limited to by car and on foot as public transportation is of limited use in a tornado evacuation given the limited number of routes and frequent stops for public transportation and the short lead time of tornadoes (less than 15 minutes on average (Strader et al. 2021)). Additionally a study on mobile home residents in the southern US by Schmidlin et al. (2009) suggested people will drive to shelters if they are further than 200 m and walk otherwise. Pedestrian speeds follow the logic of Wang et al. (2016) and are assigned to each agent based on a random draw from a normal distribution where the mean speed is 5.4 km/h (corresponding to a fast walk) and the standard deviation is 0.7 km/h yielding a typical range from a slow walk (3.6 km/h) to slow run (7.2 km/h).

We add background traffic agents to the road network to represent cars that are on the road but not participating in the evacuation (e.g., passing through the study area). Due to computational restraints, we were unable to simulate the full population of the city of Norman and adding background traffic was a simple way to adjust evacuation times during rush hour and other busy traffic periods. The background traffic agents start at one terminal network point on a road and typically travel to the opposite terminal network point on the same road, however 20% will choose a random alternate terminal point as their destination. The waiting time for the next background traffic agents to be added to the road network varies according to the following equation.

$$w_h = floor\left(w_{pt}\left(\frac{p_{pt}}{p_h}\right)\right) \tag{1}$$

where w_{pt} is the pre-defined waiting time at the peak traffic time, p_{pt} is the percentage of agents who are on the road at the peak traffic hour, and p_h is the percentage of agents who are on the road at the simulated hour. For these simulations, we assume the tornado warning is issued on a weekday when the typical peak traffic hour is 1700 LT. We set w_{pt} to 10 s as multiple tests have indicated that a waiting time of 10 s yields a reasonable rush hour traffic pattern. The background traffic agents neither respond to the tornado warning nor are impacted by the tornado hazard but instead act only as a barrier for the movement of the agents to represent how the time of day can influence traffic levels and thus the potential time required to take protective action.

Decision-making and protective action

The tornado warning decision making process is a complex social process that begins with the issuance of a tornado warning by the National Weather Service (NWS) and ends with the public making a decision about whether or not to take protective action and which action to take if any (Brotzge and Donner 2013). The agent goes through a five-step process to make their protective action decision: (1) assesses the credibility of the threat as well as their ability to take action and the efficacy of such action, (2) checks to see if they receive the warning, (3) attempts to understand the warning and the risk to their life, (4) decides whether to respond or not, and (5) decides the protective action to take, if any (Brotzge and Donner 2013). Each decision is treated as a random weighted draw from a set of decisions based on their attendant probabilities. For example, if an agent has a 90% chance of receiving a tornado warning they would perform a weighted random draw where 90% of the time they would receive the warning and 10% of the time they would not.

Agents who have decided to take protective action then make a second decision regarding the type of action to take: monitor the situation, seek refuge, seek shelter, or evacuate. TWISTER ABM allows for eight different scenarios regarding the type of protective action each agent takes: (1) everyone who responds to the warning (responders) seeks refuge, seeks shelter, or evacuates, (2) all responders evacuate, (3), all responders shelter-in-place (seek refuge only), (4) all responders seek shelter only, (5) all agents evacuate, (6) all agents shelter-in-place, (7) all agents seek shelter, (8) all agents do nothing. Scenario 1 represents the normal situation where people have a choice in which action they take (Ripberger et al. 2019), while the other scenarios represent extreme cases where everyone either has a choice between doing nothing and one specified action or everyone responds to the warning in one specified way.

The agents make one final decision as they are travelling towards their protective action destination. If they see the tornado directly ahead of them (within 5 km), and it appears closer than the distance to their destination, they make a decision on whether to continue to their destination along their current route or to change the route to their destination or their destination itself. We assume the tornado is visible at a distance of 5 km as the average human can see about 5 km due to the Earth’s curvature (Burke 2020) and that obstruction due to rainfall or hail might limit sight beyond the horizon (Edwards 2021)). To make this decision they perform a random binary draw weighted by their risk aversion parameter. If they draw ‘yes’, they attempt to find a new route to their chosen destination that avoids the tornado. If such a route cannot be found, they turn around and choose a new destination in the opposite direction of the tornado. See Appendix 6 for more details about the decision-making process.

Tornado hazard

The tornado hazard in TWISTER ABM is simulated as a separate agent that moves across the study area impacting buildings and resident agents as it moves. The tornado hazard is comprised of the agent (representing the center of the tornado) and its attendant wind field. The wind field decreases in intensity away from the agent until it reaches the tornado’s maximum radius and the proportion of the wind field at each intensity level (EF-scale) is described by the Nuclear Regulatory Commission’s (NRC) tornado wind field model (Ramsdell et al. 2007). In the NRC model, only a fraction of the area of a tornado is covered by the strongest winds. For example, for an EF5 tornado, 53.8% of the area experiences EF0 level winds while only 1.7% experiences EF5 level winds. To determine the spatial extent of each wind intensity level we calculate the radius of each level surrounding the tornado as defined by the following equation.

$$r_m = \left(\sum_{i=5}^{m} A_i\right) \times r_0 \qquad (2)$$

where m is the EF level of the radius you want to calculate, A_i is the percentage of the tornado’s area covered by winds at the ith EF level (defined in the EF Wind Field file, see Supplemental Information for full details), r_0 is the radius of the EF0 winds (half the maximum width of the tornado), and m is EF level. As the tornado moves across the study area it impacts any buildings that fall within its wind field. Depending upon the intensity of the winds that each building experiences they may suffer damage. Each building has a maximum EF level that it can withstand (see Supplemental Information for full details), once that level is exceeded for a building it is considered destroyed. For example, a one- to two-family home experiences total destruction at EF4 level winds (McDonald and Mehta 2006); thus, any one- to two-family home experiencing EF4 level winds or higher will be destroyed. The path that the tornado takes across the study area can be set by the user by clicking on the interface at any two points representing the starting and ending points for the tornado. If the user doesn't select the starting and ending points, the tornado defaults to starting in the southwest corner of the study area and ends in the northeast corner. As tornadoes tend to move from southwest to northeast in Oklahoma (Suckling and Ashley 2006), we use the default setting for this study. See Table 2 for a listing of key variables for the tornado agents.

Fatalities

Resident agents can be killed if they are in a destroyed building, a tipped car, or are lofted by the tornado. Once an agent becomes impacted by the tornado's wind field the agent immediately stops moving (we do this for simplicity, but we assume any person experiencing a tornado would stop and shelter as best they can wherever they are once the tornado hits). We assess the fatality status of the agent based on the maximum EF level winds they experience as well as the agent's location at the time of impact. Agents who are in a FEMA-rated shelter or who have reached their evacuation point (successfully escaped the at-risk area) are assumed to be safe. Agents who are inside a building (either seeking refuge or not) are safe if the building is not destroyed. If the building is destroyed, a random binary draw is performed weighted by the type of building the agent is in (20% for mobile homes (Brooks and Doswell 2002) or 1% for other buildings (Brooks et al. 2008; Prevatt et al. 2012). For example, an agent who is inside a one- to two-family home that is destroyed has a 1% chance of being killed (drawing 'yes'). Agents who are inside a car are assumed killed if the car is tipped. Studies by Schmidlin et al. (2002) and Paulikas and

Schmidlin (2017) have suggested that about 4%, 15%, and 31% of cars will tip over in EF1 – EF2, EF3 – EF4, and EF5 level winds respectively. We use those percentages as probabilities that a car will be tipped if it is impacted by the respective wind intensities. A binary random draw weighted by the wind intensity level (4% for EF1 – EF2, 15% for EF3 – EF4, and 31% for EF5 level winds) is performed to determine if the car is tipped and the agent killed. For example, an agent in a car experiencing EF4 level winds has a 15% chance of their car being tipped and them being killed (drawing a 'yes'). Agents who are outside are assumed killed if the wind is strong enough to loft them (overcome the force of gravity) which happens around 177 – 217 km/h (Long and Weiss 1999; Agrawal 2000) (*i.e.*, EF2 – EF3 level winds (McDonald and Mehta 2006)). For our model, we assume agents who are outside are lofted at EF2 level winds. While people have survived being lifted by tornadoes (Katsura and Conner 2002), it is assumed that most would not be due to the potential damage to the body from debris as well as the damage done by the fall afterward (Ono 2002). For simplicity, we do not consider indirect fatalities (*e.g.*, death due to a fire in a damaged home (Brown et al. 2002)) and assume fatalities only occur in the path of tornado.

Sensitivity analyses and model validation

To showcase TWISTER ABM's performance, we conducted several sensitivity analyses to determine how the model responded to variations in tornado intensity (EF level), lead time, time of day (for a weekday), percentage of residences with shelters, and number of public shelters. For all analyses (except where we are varying the specified parameter), we set the parameters as defined in Table 3.

We vary the parameters for the sensitivity analyses as described in Table 4. We perform Kruskal-Wallis tests to determine if there were significant differences between the group medians for the fatality rate, mean trip duration for trips to refuges, shelters and evacuation points, and mean response rate between the dependent variables (*e.g.*, tornado intensity). If significant differences were found ($p \leq 0.05$), we then performed the post-hoc Dunn test (with Bonferroni adjustment) (Dunn 1964), to determine which groups were different. We chose the non-parametric Kruskal-Wallis test as many of the model output variables are non-normal for at least some of the groups. The Dunn test is a common post-hoc test for use with the Kruskal-Wallis test and we use the Bonferroni adjustment to the p-value to help reduce the probability of committing a type I error (Dinno 2015).

We validate the model in two ways: comparing model travel time to expected trip duration (estimated from Google Maps data) and by comparing the simulated fatality rate (per 1000 residents (‰)) living within the tornado's path) with the observed fatality rate for all significant (EF2-3) and violent (EF4-5) tornadoes that hit within 100 km of Oklahoma between 1995 and 2020. For the travel time validation, we set the scenario to Scenario 5 (all agents evacuate) and simulate two times of day (0200 LT and 1700 LT) to test travel time when traffic is near the minimum and maximum. We set the number of agents to 100 and allowed them to choose their own route to the nearest evacuation point. All other parameters are as in Table 1. After the simulations completed, we used the Google Directions API (Google 2022) via the mapsapi package in R (Dorman 2022) to calculate the estimated travel times, between the agent's starting and ending points at 0200 LT and 1700 LT, using the pessimistic, optimistic, and best guess traffic models to get a range of possible travel times. When the Google Directions API detected multiple routes between the starting and ending points, we calculated the mean travel time over all routes. While TWISTER ABM's traffic flow is overly simplified, we felt justified in using Google Maps data as we were only interested in comparing travel times and not overall traffic flow. Using Google Maps data we could ensure our travel times were realistic. We conducted a paired Mann-Whitney test (Mann 1945; Mann and Whitney 1947) to determine if the simulated and best guess travel times were statistically similar. We also calculated Pearson's correlation coefficient between the simulated and best guess travel times to determine the degree of association between the two and tested how often the simulated travel time fell between the pessimistic and optimistic travel times.

For the fatality rate comparison, we start by selecting all tornado tracks for significant and violent tornadoes, which occurred between 1995 and 2020, from the Storm Prediction Center's SVRGIS database (SPC 2021). While we only use 2019 demographic data from the city of Norman, Oklahoma for the agent specification, we felt justified in using 1995-2020 tornado fatality data as we needed more than one year's worth of data for our analysis and a Kruskal-Wallis test showed no significant differences between the fatality rates for the three decades ($H = 1.152$, $p = 0.562$, $df = 2$). Using the sf package in R we estimated the damage path of each tornado by creating a spatial buffer around the tornado tracks (the buffer width corresponded to the reported tornado width). We then selected only the damage paths that fell within 100 km of the state of Oklahoma and estimated the population residing in each path. We performed the same task for each of the significant and violent tornadoes simulated during the tornado intensity sensitivity test. To determine the population residing in the path we first created a 1 km resolution grid across a 100 km spatial buffer surrounding the state of Oklahoma and estimated the population in each grid cell for the 1990, 2000, 2010, and 2020 censuses (Manson et al. 2021) using area-weighting (following the methodology of Ashley et al. (2014)). We then estimate the population in the grid for the year of the tornado by linear interpolation between the preceding and following census, years assuming a constant trend, as follows

$$P_Y = \begin{cases} P_{C1} + \frac{Y-Y_{C1}}{10}(P_{C2} - P_{C1}), \ Y < 2020 \\ P_{2010} + \frac{Y-2010}{10}(P_{2020} - P_{2010}), \ Y \geq 2020 \end{cases} \quad (3)$$

where Pop_{C1} and Pop_{C2} are the populations in the preceding and following census years respectively, P_{2010} and P_{2020} are the populations in 2010 and 2010 respectively, Y is the year of the tornado and Y_{C1} is the year of the preceding census. For each tornado, we performed a spatial intersection between the tornado path and the population grid and summed the population across the path. For the simulated tornadoes we assume the year is 2020. Once we have the population impacted by each tornado, we estimate the fatality rate as the number of fatalities divided by the population in the path (represented as fatalities per 1000 residents or ‰). We perform a Mann-Whitney test to determine if the mortalities are different between the observed and simulated significant and violent tornadoes and compare the summary statistics for fatality rate as well.

Effectiveness of shelter-in-place

To determine how the National Weather Service's recommended protective action paradigm (shelter-in-place) compared to other protective action paradigms we ran a series of simulations in TWISTER ABM for each of the following scenarios: (1) everyone who responds to the warning (responders) seeks refuge, seeks shelter, or evacuates, (2) all responders evacuate, (3), all responders shelter-in-place, (4) all responders seek shelter only, (5) all agents evacuate, (6) all agents shelter-in-place, (7) all agents seek shelter, (8) all agents do nothing. We set all parameters, except the scenario which we varied, as in Table 1. We perform Kruskal-Wallis tests to determine if there were significant differences between the group medians for the fatality rate, mean trip duration for trips to refuges, shelters and evacuation points, and mean response rate between the scenarios. If significant differences were found ($p \leq 0.05$), we then performed Dunn tests (with Bonferroni adjustment), to determine which groups were different.

Results

General model behavior

Fig. 4 shows the model progression for a typical run of the TWISTER ABM (parameters set as in Table 3) starting with the issuance of a tornado warning at time t = 0 minutes. Fig. 4a shows the initial distribution of the agents (dots) at the simulated time (1700 LT on a weekday) based on typical daily migration patterns (as defined by the American Time Use Survey). At this time, 53% of the agents are at home, 27% are at work, 8% are on the road, and the rest are visiting friends, running errands/shopping or doing outdoor activities in a park. By seven minutes (Fig. 4b) the milling period has ended for many agents, and they have begun to take protective action. By this time many have already completed their protective action (diamonds). By 15 minutes (Fig. 4c), the tornado has formed outside the study area (black triangle) and by 20 minutes (Fig. 4d) it has entered the study area causing the first fatalities (x's). The grey shading represents the damage path of the tornado with darker shades of grey indicating greater damage (stronger winds). The tornado continues to track through the study area (Fig. 4e) causing more fatalities until it exits the area (Fig. 4f) and dissipates at around 28 minutes. At the end of the simulation the total number of fatalities and the time it took each agent to complete their protective action (if they chose to act) are calculated to assess the severity of the simulated event. For this example simulation, there were 29 fatalities (7.3 fatalities per 1000 agents) and the mean time to complete a protective action was 14.1 minutes.

Model validation

Fatality rate

The mean number of fatalities for significant (EF2-3) and violent (EF4-5) tornadoes hitting within 100 km of Oklahoma between 1995 and 2020 was 0.6 and 6.6 fatalities respectively (Fig. 5). The corresponding mean fatality rates were 1.8 fatalities per 1000 residents (‰) and 3.3‰ respectively. The mean number of fatalities for simulated significant and violent tornadoes in Norman, Oklahoma in 2020 were 4.3 and 15.2 fatalities respectively. The corresponding mean fatality rate was 1.3‰ and 2.2‰ respectively. We find that TWISTER ABM overestimates the mean number of fatalities but underestimates the maximum number of fatalities as well as the mean fatality rate. A Mann-Whitney test confirmed that the observed and simulated mortalities for significant tornadoes were statistically different ($W = 832$, $p < 0.001$); however, it also showed that the mortalities for violent tornadoes were similar ($W = 177$, $p = 0.33$). We believe that the shorter simulated tornado paths (9.5 km (for all simulated tornadoes) vs 26.9 km for observed significant and 50.1 km for observed violent tornadoes) may explain the lower maximum mortalities for simulated tornadoes. While the mean mortalities are different between the simulated and observed tornadoes, the overall distribution of the simulated mortalities does fall within that of the observed mortalities. We maintain that this fact, combined with the statistical similarity between the simulated and observed violent tornado mortalities, imply that TWISTER ABM produces reasonable fatality estimates.

Travel time

To validate TWISTER ABMs ability to accurately capture travel times between locations within the study area we compared simulated travel times (to the nearest evacuation point) for 100 random agents to the estimated travel times from the Google Directions API (using the best guess traffic model) (Google 2022) for the same trips. A paired Mann-Whitney test showed that the simulated and estimated travel times were statistically different for travel at both 0200 LT ($V = 4831.5, p < 0.001$) and 1700 LT ($V = 3898.5, p < 0.001$). While the estimated and simulated travel times are statistically different, we find that the Pearson's correlation coefficient is strong ($R^2 = 0.71$) at 0200 LT and moderate ($R^2 = 0.65$) at 1700 LT (Fig. 6). We also find that the simulated travel time falls between the estimated travel times, using the pessimistic and optimistic traffic models, 27% of the time at 0200 LT and 55% of the time at 1700 LT. Given that TWISTER ABM assumes a simplified road network with one-lane roads and 55 km/h speed limits, we maintain that model simulates travel time reasonably well.

Sensitivity tests

Tornado intensity and width

Fig. 7 shows the sensitivity of the fatality rate, mean trip duration, and the response rate to the tornado intensity and width. The mean fatality rate varied from 0‰ (EF0) to 4.8‰ (EF5) with minimum and maximum mortalities of 0‰ (EF) and 9.8‰ (EF5) respectively. A Kruskal-Wallis test showed that the fatality rate was sensitive to changes in the tornado intensity ($H = 109.46$, $p < 0.001$, $df = 5$). The post-hoc Dunn test showed that the fatality rate significantly increased between EF0 and EF3 ($p < 0.001$) and between EF3 and EF5 ($p = 0.008$). The mean of the mean trip durations varied between 3.0 (EF0) and 3.4 minutes (EF4) with minimum and maximum mean trip durations of 2.9 (EF0) and 3.8 minutes (EF5) respectively. The mean trip duration was also sensitive to changes in tornado intensity ($H = 53.92$, $p < 0.001$, $df = 5$) with significant increases in duration between EF0 and EF3-5 ($p < 0.001$), EF1 and EF3 (($p = 0.007$), EF1 and EF4-5 ($p < 0.001$) and EF2 and EF4=5 ($p = 0.002$). The mean response rate varied from 56.9% (EF0) to 62.2% (EF5) with minimum and maximum response rates of 55.3% (EF0) and 64.1% (EF5) respectively. The response rate was sensitive to tornado intensity as well ($H = 88.96$, $p < 0.001$, $df = 5$) with significant increases in the rate between EF0 and EF3 ($p < 0.001$) and EF2 and EF5 ($p = 0.002$). While for each output variable the differences between the values for each consecutive EF level were not always significant, the general trend for each variable was an increase with increasing tornado intensity.

Time of day

Fig. 8 shows the sensitivity of the fatality rate, mean trip duration, and the response rate to the time of day. The mean fatality rate varied from 5.2‰ (0100 LT) to 6.2‰ (2100 LT) with maximum and minimum mortalities of 3‰ (0100 LT) and 10.5‰ (2100 LT) respectively. The fatality rate was not sensitive to the time of day ($H = 3.38$, $p = 0.64$, $df = 5$). The mean of the mean trip durations varied from 3.2 (1300 LT) to 3.7 minutes (0500 LT) with minimum and maximum mean trip durations of 2.9 (0900 LT) and 4.1 minutes (0500 LT) respectively. The mean trip duration was sensitive to the time of day ($H = 71.85$, $p < 0.001$, $df = 5$) with significant decreases between each of 0900 LT and 2100 LT ($p < 0.001$), 1300LT and 2100 LT ($p < 0.001$), and 1700LT and 2100 LT ($p = 0.02$) and significant increases between 0100 LT and 0900LT ($p < 0.001$), 0100 LT and 1300 LT ($p < 0.001$), 0100 LT and 1700 LT ($p = 0.002$), 0500 LT and 0900 LT ($p < 0.001$), 0500 LT and 1300 LT ($p < 0.001$), 0500 LT and 1700 LT ($p = 0.002$). The mean trip duration followed the mean trip distance with greater distances (and durations) in the evening and overnight hours. The mean response rate varied from 41.4% (0100 LT) to 61.9% (1700 LT) with minimum and maximum response rates of 39.8% (0100 LT) and 63.2% (1700 LT) respectively. The response rate is also sensitive to time of day ($H = 107.80$, $p < 0.001$, $df = 5$) with a significant increase between 0100 LT and 1300

LT ($p < 0.001$) and a significant decrease between 1700 LT and 2100 LT ($p < 0.001$). We found the response rate was lowest when more agents were at home asleep (0100 LT – 0500 LT) and highest when more people were at home awake (1700 LT).

Lead time

Fig. 9 shows the sensitivity of the fatality rate, mean trip duration, and the response rate to the lead time. The mean fatality rate varied from 4.5‰ (60-minute lead time) to 6.0‰ (5-minute lead time) with minimum and maximum mortalities of 1.8‰ (60-minute lead time) and 12‰ (15-minute lead time) respectively. The fatality rate was sensitive to the lead time ($H = 13.39$, $p = 0.02$, $df = 5$) with a significant decrease between 5- and 60-minute lead times ($p = 0.01$). The mean of the mean trip durations varied from 2.8 (0-minute lead time) to 4.3 minutes (60-minute lead time) with minimum and maximum mean trip durations of 2.6 (0-minute lead time) and 6.5 minutes (60-minute lead time) respectively. The mean trip duration was sensitive to the lead time ($H = 98.07$, $p < 0.001$, $df = 5$) with significant increases between 0 and 15-60 minutes ($p < 0.001$), 5 and 30-60 minutes ($p < 0.001$), and 15 and 45-60 minutes ($p < 0.005$). The mean response rate varied between 45.7% (0-minute lead time) and 65.4% (60-minute lead time) with maximum and minimum response rates of 44.2% (0-minute lead time) and 67.2% (45-minute lead time) respectively. The response rate is also sensitive to lead time ($H = 106.44$, $p < 0.001$, $df = 5$) with significant increases between 0 and 15 minutes ($p = 0.002$) and 15 and 60 minutes ($p < 0.001$).

Shelter availability

Fig. 10 shows the sensitivity of the fatality rate, mean trip duration, and the response rate to the percentage of residential buildings with shelters. The mean fatality rate varied from 5.0‰ (40%

of residences) to 6.2‰ (1% of residences) with minimum and maximum mortalities of 2.5‰ (10% and 20% or residences) and 10.5‰ (1% of residences) respectively. The fatality rate was not sensitive to the percentage of residential buildings with shelters ($H = 7.59$, $p = 0.18$, $df = 5$). The mean of the mean trip durations varied from 3.2 (80% of residences) to 3.4 minutes (5% of residences) with minimum and maximum mean trip durations of 3.0 (80% of residences) and 3.9 minutes (5% of residences) respectively. The mean trip duration was sensitive to the percentage of residential buildings with shelters ($H = 25.44$, $p < 0.001$, $df = 5$) with a significant decrease between 5% and 80% ($p < 0.001$), 10% and 80% ($p < 0.001$), and 20% and 80% ($p = 0.02$). We expected that increasing the number of residential shelters would reduce travel time as agents who were seeking shelter had more options. Those agents who were at home when they made their decision would be less likely to have to leave home to reach a shelter as the number of residential shelters increased. The mean response rate varied from 61.8% (80% of residences) to 62.1% (5% and 10% of residences) with minimum and maximum response rates of 60.0% (5% of residences) and 64.3% (80% of residences) respectively. The response rate is not sensitive to the percentage of residential buildings with shelters ($H = 4.32$, $p = 0.50$, $df = 5$). We did not expect the response rate to be impacted by the number of residential shelters as residential shelters are only available to the occupant of that residence and increasing residential shelters would not make more shelters available for each agent.

Fig. 11 shows the sensitivity of the fatality rate, mean trip duration, and the response rate to the number of public shelters. The mean fatality rate varied from 5.0‰ (1000 and 1800 shelters) to 5.6‰ (50 shelters) with minimum and maximum mortalities of 2.5‰ (200 shelters) and 9.3‰ (5 shelters) respectively. The fatality rate was not sensitive to the number of public shelters ($H = 4.12$, $p = 0.53$, $df = 5$). The mean of the mean trip durations varied from 2.8 (1000 shelters) to

2.3 minutes (5 and 20 shelters) with minimum and maximum mean trip durations of 2.7 (1000 shelters) and 3.7 minutes (5 shelters) respectively. The mean trip duration was sensitive to the number of public shelters ($H = 94.48$, $p < 0.001$, $df = 5$) with significant increases between 5 and 200+ shelters ($p < 0.001$), 20 and 200+ shelters ($p < 0.001$), 50 and 200 shelters ($p = 0.02$), and 50 and 1000+ shelters ($p < 0.001$). The mean response rate varied from 62.0% (50 and 1000 shelters) to 62.3% (1800 shelters) with minimum and maximum response rates of 60.3% (200 shelters) and 64.8% (200 shelters) respectively. The response rate is not sensitive to the number of public shelters ($H = 4.62$, $p = 0.46$, $df = 5$). While not statistically significant, these findings are also in line with the literature which suggests that the presence of shelters reduces fatalities (Merrell et al. 2002; Simmons and Sutter 2007) and increases in shelter availability can lead to increased self-efficacy which can increase tornado warning response (Ash 2017; Huntsman et al. 2021; Jauernic and Van Den Broeke 2017).

Effectiveness of shelter-in-place

To determine how effective shelter-in-place was at reducing fatality rate and travel time, compared to other protective action paradigms, we ran a series of simulations in TWISTER ABM for each of the scenarios 1 – 8. The results can be found in Fig. 12. Through a series of Kruskal-Wallis tests, we found that the fatality rate ($W = 115.0$, $p < 0.001$, $df = 7$) and mean completion time (time required to reach the selected protective action destination; $W = 127.4$, $p < 0.001$, $df = 6$) were sensitive to the selected protective action scenario. The overall fatality rates, among all scenarios, for agents by protective action type were 5.5‰ (taking no action), 3.3‰ (seeking refuge in the nearest sturdy building), 15.3‰ (seeking shelter in a FEMA-rated shelter), and 10.5‰ (fleeing the area). The fatality rate was lowest for Scenario 6 (everyone shelters-in-place; 2.4‰) and highest for Scenario 4 (all of those who respond to the warning seek shelter; 15.4‰; this difference was statistically significant by a Dunn test ($p < 0.001$)), a 6.6x reduction in fatality rate for the shelter-in-place scenario. The high fatality rate in Scenario 4 was a result of all responding agents seeking shelter in their own homes (if they have a shelter) or in a limited number of public shelters (20). This resulted in significant traffic jams leading to the shelters and meant more people were stuck on the road when the tornado hit. Two of the three lowest mortalities were for shelter-in-place scenarios; however, interestingly, the second lowest fatality rate (4.0‰) was for the scenario where no one responds. While this may seem counterintuitive, the fact that most agents (who are not taking protective action) are indoors means that most agents have some protection from the tornado, reducing the likelihood of death.

The mean of the mean completion times was highest for Scenario 2 (14.3 minutes) and lowest for Scenario 6 (6.7 minutes; this difference was significant by a Dunn test ($p < 0.001$)). Scenarios 4 and 7 have some of the lowest mean completion times (9.2 and 7.4 minutes respectively); however, they also have the lowest mean completion rates (percentage of agents who complete their protective action; 15.6% and 18% respectively). This is because so many of the agents were traveling to the same sheltering destination creating large traffic jams allowing fewer agents to reach their destinations. Scenario 6 had the greatest mean percentage of agents completing their protective action by the time the lead time expired (within 15 minutes; 93%) while Scenario 4 had the lowest mean percentage (11.7%; other than for Scenario 8 when no one responded). For each simulation in the experiment, nearly half, or more, of the agents who successfully completed their protective action by the end of the model run, did so before the tornado formed.

Discussion and Conclusion

We developed the Tornado Warning-Induced Shelter, Travel, and Evacuation Response Agent-Based Model (TWISTER ABM) as a framework for studying protective action behaviors during tornado warnings. We found that the simulated fatality rate was sensitive to changes in tornado intensity and width, and lead times but not sensitive to start times or the number of shelters available.

The increase in simulated fatality rate with increasing tornado intensity was in line with the literature which suggests that stronger tornadoes cause more fatalities (Agee and Taylor 2019; Anderson-Frey and Brooks 2019; Fricker 2020), cause more people to flee the building they are in (to find a safer location) (Ash et al. 2020; Casteel 2018), and are more likely to prompt a person to take protective action (Casteel 2018; Johnson et al. 2021).

It is not surprising that the fatality rate was not sensitive to the time of day as there is much uncertainty on whether an agent will find themselves in the path of the tornado. We expected the fatality rate to be highest around 1700 LT when rush hour traffic would increase trip duration, and lowest between 0100 LT and 0500 LT when more people would be inside asleep. While the fatality rate was high at 1700 LT, we found the highest fatality rate at 2100 LT and high mortalities during the overnight hours. These results follow the findings in the literature which states that nocturnal tornadoes are more likely to cause fatalities (Ashley et al. 2008; Simmons and Sutter 2009), less likely to be warned (Anderson-Frey and Brooks 2021), and less likely to be responded to (Krocak et al. 2021; Mason et al. 2018) than those that occur during the day. Also, in the model, people are more likely to leave their homes to seek shelter elsewhere in the evening than during the day. This led to greater trip distances and durations putting the agents at greater risk and leading to a higher fatality rate. The increase in the duration during the day was due to increases in the likelihood of evacuation with more agents on the road traveling home from work.

We expected shorter lead times to result in greater fatality rate as the agents would have less time to take protective action. It was interesting that the mean fatality rate was highest at a 5-minute lead time and the maximum value was highest at a 15-minute lead time. We believe that that the higher fatality rate at these times were because more agents had time to begin traveling which increased their risk by placing them outside or on the road. There is no physical reason why the mean trip duration should increase with lead time; however, we assume this increase is due to the increase in the number of agents responding.

We expected the response rate to increase with lead time as the agents had more time to take action. These findings are in line with the literature which suggests that greater lead time results in fewer fatalities and greater response rates (Hoekstra et al. 2011; Simmons and Sutter 2008). In the model, lead time does not influence the decision-making process, it merely gives the agents longer to respond before the tornado arrives. This results in greater response rates for each increase in lead time. In reality, lead times longer than 15-30 minutes can result in people underestimating their risk and waiting until it is too late to respond (Simmons and Sutter 2008).

We expected that increasing the number of residential shelters would reduce the fatality rate at least somewhat. It is not surprising that the difference is not significant as each agent can only go to a shelter in their own home no matter how many residential shelters exist.

Our sensitivity tests showed that fatality rate, trip completion times, and response rates behave as expected with varying tornado intensities, lead times, and start times. We also showed that

TWISTER ABM produces reasonable mortalities and travel times when compared to real world data.

We found that both shelter-in-place scenarios (all responding agents shelter-in-place (Scenario 3) and everyone shelters-in-place (Scenario 6)) were in the bottom three in terms of fatality rate and mean completion times. Conversely, we found that both scenarios where agents traveled to FEMA-rated shelters (all responding agents seek shelter (Scenario 4) and all agents seek shelter (Scenario 7)) were the highest in terms of fatality rate with less than 25% of agents completing their trips to shelter. This suggests that shelter-in-place does indeed save lives (reduces fatalities by a factor of 6.6 compared to seeking shelter in a FEMA-rated shelter), while having many people travel to a limited number of shelters can cause traffic to slow down significantly and leave more people exposed in vehicles to an approaching tornado. Many communities in the state of Oklahoma, including Norman, have recognized this fact and closed all public shelters (Dean 2013). Our finding that Scenario 8 (where no agents respond) had the second lowest fatality rate was concerning; however, the fact that most people stayed indoors in this scenario may explain why the fatality rate was so low. Studies have indicated that even in violent tornadoes, the per building fatality rate for destroyed one- to two-family homes is only 0.1% - 1.9% (Brooks et al. 2008; Prevatt et al. 2012). Among the building types that the NWS uses as damage indicators, for its tornado damage surveys, only small barns and outbuildings and single-wide and double-wide mobile homes suffer catastrophic damage in EF2 level winds (McDonald and Mehta 2006). Less than 5% of reported tornadoes between 1950 and 2020 have had maximum intensities greater than EF2 (SPC 2021) and of those only an estimated 7% (EF3) – 12% (EF5) of their damage path area experienced wind speeds exceeding 217 km/h (EF3+ level) (Ramsdell et al. 2007). Despite the likelihood of death in mobile homes being considerably higher (15 – 20 times higher than for permanent homes according to studies by Brooks and Doswell (2002) and Simmons and Sutter (2010)), it would not be surprising for most people in tornado-impacted buildings to survive given less than 0.1% of the city of Norman is zoned for mobile homes (City of Norman 2021).

One limitation of this study is that in the model is that there is no distinction between agents who are indoors and seeking refuge and those who are just indoors. This distinction was omitted from the model as the authors are aware of no studies on indoor fatality rates that distinguish between those who were seeking refuge and those who were not. In reality, a person who is asleep in bed is likely at greater risk than someone who is seeking refuge in an interior room on the lowest level in the house. Studies on tornado-related fatality rate suggest that being struck by an object, thrown, or crushed by rubble are the leading causes of death in a tornado and these sorts of injuries are more likely when one is prone and near an exterior wall (Daley et al. 2005; Chiu et al. 2013).

Another limitation of this study is in the damage indicator assignment method used for the building points dataset. We make a few simple assumptions regarding how the damage indicator relates to the building's size and zoning classification. We chose a simple method for illustration purposes; however, more rigorous approaches (e.g., machine learning algorithms) could be applied to assess the damage indicator more accurately for each building in the study area. Kim et al. (2022) used a random forest algorithm to assess the building type for residential buildings in Oklahoma City, OK. Such a method could potentially be adapted to assess building types for other municipal zones (e.g., industrial, commercial) in other cities. While our approach was simple, we believe that, given that most buildings do not suffer maximum damage until they experience EF4+ level winds (McDonald and Mehta 2006) and most buildings in the model will not be destroyed until the wind speed reaches EF4 level, the building dataset is representative of the real world. Additionally, for simplicity, we assume that all non-residential buildings are open to the public at the time of the tornado. In reality, most commercial buildings are only open during certain hours of the day and other buildings, such as factories and government buildings, may not be open to the public at any time. We used this assumption as we had no information on building hours or the type of activity conducted within the buildings. Future studies may address this limitation by identifying the locations of businesses within the city of Norman to have a better idea of building availability.

In the model runs for this study, agents can only shelter in a residential building it is their home. In reality, neighbors and friends will sometimes allow a person to shelter in their home or storm shelter. TWISTER ABM has the capability to extend residential shelter availability to include neighboring residences or random residences (to represent friends' homes). Future studies will investigate how changing the residential shelter availability influences fatality rate. Such studies could determine if encouraging neighbors to open their homes could result in significantly fewer fatalities**.** The Tornado Warning-Induced Shelter, Travel, and Evacuation Response Agent-Based Model shows promise as a tool for studying travel behavior during tornado warnings. Our sensitivity tests showed that fatality rate, trip completion times, and response rates behave as expected with varying tornado intensities, lead times, and start times. We also showed that TWISTER ABM produces reasonable mortalities and travel times when compared to real world data. We used TWISTER ABM to quantify the value of the National Weather Service's shelter-in-place paradigm in saving lives. We believe that tools like TWISTER ABM can be used to better inform emergency managers on the risks and potential consequences of traveling when tornado warnings are active. Such knowledge can help emergency managers improve their planning with regard to opening public shelters and how they communicate risk to the public.

Data Availability Statement

All data and code used in the analysis (including the TWISTER ABM model code) are available upon reasonable request from the authors.

Acknowledgements

Funding was provided by NOAA/Office of Oceanic and Atmospheric Research under NOAA-University of Oklahoma Cooperative Agreement #NA16OAR4320115, U.S. Department of Commerce.

References

Agee, E., and L. Taylor. 2019. “Historical analysis of U.S. Tornado fatalities (1808–2017): Population, science, and technology.” *Weather Clim. Soc.*, 11 (2).

Agrawal, D. C. 2000. “Terminal velocity of skydivers.” *Physics education*, 35 (4): 281.

Anderson-Frey, A. K., and H. Brooks. 2019. “Tornado fatalities: An environmental perspective.” *Weather Forecast.*, 34 (6): 1999–2015.

Anderson-Frey, A. K., and H. Brooks. 2021. “Compared to what? Establishing environmental baselines for tornado warning skill.” *Bull. Am. Meteorol. Soc.*, 102 (4): E738--E747.

Ash, K. D. 2017. “A qualitative study of mobile home resident perspectives on tornadoes and tornado protective actions in South Carolina, USA.” *GeoJournal*, 82 (3): 533–552.

Ash, K. D., M. J. Egnoto, S. M. Strader, W. S. Ashley, D. B. Roueche, K. E. Klockow-McClain, D. Caplen, and M. Dickerson. 2020. “Structural forces: Perception and vulnerability factors for tornado sheltering within mobile and manufactured housing in Alabama and Mississippi.” *Weather Clim. Soc.*, 12 (3): 453–472.

Ashley, W. S., A. J. Krmenec, and R. Schwantes. 2008. “Vulnerability due to nocturnal tornadoes.” *Weather Forecast.*, 23 (5): 795–807.

Ashley, W. S., S. M. Strader, T. Rosencrants, and A. J. Krmenec. 2014. “Spatiotemporal changes in tornado hazard exposure: The case of the expanding bull’s-eye effect in Chicago, illinois.” *Weather Clim. Soc.*, 6 (2): 175–193.

Beloglazov, A., M. Almashor, E. Abebe, J. Richter, and K. C. B. Steer. 2016. “Simulation of wildfire evacuation with dynamic factors and model composition.” *Simul. Model Pract. Theory*, 60: 144–159.

Black, A. W., J. A. Knox, J. A. Rackley, and N. S. Grondin. 2019. “Tornado Debris from the 23 May 2017 ‘Tybee Tornado.’” *Bull. Am. Meteorol. Soc.*, 100 (2): 217–222.

Blair, S. F., and E. P. K. Lunde. 2010. “Tornadoes impacting interstates: Service and societal considerations.” *Electron. J. Sev. Storms Meteor.*, 5 (4).

Bohonos, J. J., and D. E. Hogan. 1999. “The medical impact of tornadoes in North America.” *J. Emerg. Med.*, 17 (1): 67–73.

Brooks, H. E., and C. A. I. Doswell. 2002. “Deaths in the 3 May 1999 Oklahoma City Tornado from a Historical Perspective.” *Weather Forecast.*, 17 (3): 354–361.

Brooks, H. E., C. A. I. Doswell, and D. Sutter. 2008. “Low-level winds in tornadoes and potential catastrophic tornado impacts in urban areas.” *Bull. Am. Meteorol. Soc.*, 89 (1): 87–90. https://doi.org/10.1175/BAMS-89-1-87.

Brotzge, J., and W. Donner. 2013. “The tornado warning process: A review of current research, challenges, and opportunities.” *Bull. Am. Meteorol. Soc.*, 94 (11): 1715–1733.

Brown, S., P. Archer, E. Kruger, and S. Mallonee. 2002. “Tornado-related deaths and injuries in Oklahoma due to the 3 May 1999 tornadoes.” *Weather Forecast*, 17 (3): 343–353.

Burgess, D., K. Ortega, G. Stumpf, G. Garfield, C. Karstens, T. Meyer, B. Smith, D. Speheger, J. Ladue, R. Smith, and T. Marshall. 2014. “20 May 2013 Moore, Oklahoma, Tornado: Damage Survey and Analysis.” *Weather Forecast.*, 29 (5): 1229–1237.

Burke, R. 2020. “The longest sightline on Earth.” *Calgary Vision Centre*. Accessed April 22, 2022. https://calgaryvisioncentre.com/news/2017/6/23/tdgft1bsbdlm8496ov7tn73kr0ci1q.

Carter, A. O., M. E. Millson, and D. E. Allen. 1989. “Epidemiologic study of deaths and injuries due to tornadoes.” *Am. J. Epidemiol.*, 130 (6): 1209–1218.

Casteel, M. A. 2018. “An empirical assessment of impact based tornado warnings on shelter in place decisions.” *Int. J. Disaster Risk Reduct.*, 30: 25–33.

Chandler, R. E., R. Herman, and E. W. Montroll. 1958. “Traffic dynamics: studies in car following.” *Oper. Res.*, 6 (2): 165–184.

Chen, X., J. W. Meaker, and F. B. Zhan. 2006. “Agent-based modeling and analysis of hurricane evacuation procedures for the Florida Keys.” *Nat. Hazards*, 38 (3): 321.

Chiu, C. H., A. H. Schnall, C. E. Mertzlufft, R. S. Noe, A. F. Wolkin, J. Spears, M. Casey-Lockyer, and S. J. Vagi. 2013. “Mortality from a tornado outbreak, Alabama, April 27, 2011.” *Am. J. Public Health*, 103 (8): 52–58.

City of Norman. 2021. “Zoning Map.” Accessed May 26, 2022. https://normanok.maps.arcgis.com/apps/webappviewer/index.html?id=f69b169befde4e6080f9b33cbd03f54f.

Daley, W. R., S. Brown, P. Archer, E. Kruger, F. Jordan, D. Batts, and S. Mallonee. 2005. "Risk of tornado-related death and injury in Oklahoma, May 3, 1999." *Am. J. Epidemiol.*, 161 (12): 1144–1150.

Dean, B. 2013. "Oklahoma tornadoes: Oklahoma City metro-area cities oppose public storm shelters." *The Oklahoman*. Accessed May 26, 2022. https://www.oklahoman.com/story/weather/2013/06/02/oklahoma-tornadoes-oklahoma-city-metro-area-cities-oppose-public-storm-shelters/60929198007/.

Dinno, A. 2015. "Nonparametric pairwise multiple comparisons in independent groups using Dunn's test." *Stata J.*, 15 (1): 292–300.

Dorman, M. 2022. "mapsapi: 'sf'-Compatible Interface to 'Google Maps' APIs." R package version 0.5.3. https://CRAN.R-project.org/package=mapsapi.

Doswell, C. A. I., G. W. Carbin, and H. E. Brooks. 2012. "The tornadoes of spring 2011 in the USA: An historical perspective." *Weather*, 67 (4): 88–94.

Duclos, P. J., and R. T. Ing. 1989. "Injuries and risk factors for injuries from the 29 May 1982 tornado, Marion, Illinois." *Int. J. Epidemiol.*, 18 (1): 213–219.

Dunn, O. J. 1964. "Multiple comparisons using rank sums." *Technometrics*, 6 (3): 241–252.

Durage, S. W., L. Kattan, S. C. Wirasinghe, and J. Y. Ruwanpura. 2014. "Evacuation behaviour of households and drivers during a tornado: Analysis based on a stated preference survey in Calgary, Canada." *Nat. Hazards*, 71 (3): 1495–1517.

Edwards, R. 2021. "The online tornado faq." Accessed May 22, 2022. https://www.spc.noaa.gov/faq/tornado/.

Farley, J. E. 2007. "Call-to-action statements in tornado warnings: Do they reflect recent developments in tornado-safety research?" *Int. J. Mass Emerg. Disasters*, 25 (1): 1–36.

FEMA. 2021. “Safe rooms for tornadoes and hurricanes: Guidance for community and residential safe rooms.” FEMA Washington, DC.

Fricker, T. 2020. “Evaluating tornado casualty rates in the United States.” *Int. J. Disaster Risk Reduct.*, 47: 101535.

Fricker, T., and C. Friesenhahn. 2022. “Tornado fatalities in context: 1995--2018.” *Weather Clim. Soc.*, 14 (1): 81–93.

Garfield, G., and R. Smith. 2014. “Sheltering Behavior During 2 Major Tornado Events : Is More ‘Lead Time’ Better?” *9th Symposium on Policy and Socio-Economic Research*. Atlanta, GA: American Meteorological Society.

Gensini, V. A., and H. E. Brooks. 2018. “Spatial trends in United States tornado frequency.” *NPJ Clim. Atmos.*, 1 (1): 38.

Google. 2022. “Google Directions API.” Mountain View, CA: Google.

Hammer, B., and T. W. Schmidlin. 2002. “Response to warnings during the 3 May 1999 Oklahoma City tornado: Reasons and relative injury rates.” *Weather Forecast.*, 17 (3): 577–581.

Hatzis, J. J., and K. E. Klockow-McClain. 2022. “A Spatiotemporal Perspective on the 31 May 2013 Tornado Evacuation in the Oklahoma City Metropolitan Area.” *Weather Clim. Soc.* 14(3), 721-735.

Hatzis, J. J., J. Koch, and H. E. Brooks. 2019. “Spatiotemporal analysis of near-miss violent tornadoes in the United States.” *Weather Clim. Soc.*, 11 (1).

Herman, R., E. W. Montroll, R. B. Potts, and R. W. Rothery. 1959. “Traffic dynamics: analysis of stability in car following.” *Oper. Res.*, 7 (1): 86–106.

Hoekstra, S., K. Klockow, R. Riley, J. Brotzge, H. Brooks, and S. Erickson. 2011. "A Preliminary Look at the Social Perspective of Warn-on-Forecast: Preferred Tornado Warning Lead Time and the General Public's Perceptions of Weather Risks." *Weather Clim. Soc.*, 3 (2): 128–140.

Huntsman, D., H.-C. Wu, and A. Greer. 2021. "What Matters? Exploring Drivers of Basic and Complex Adjustments to Tornadoes among College Students." *Weather Clim. Soc.*, 13 (3): 665–676.

Jauernic, S. T., and M. S. Van Den Broeke. 2017. "Tornado warning response and perceptions among undergraduates in Nebraska." *Weather Clim. Soc.*, 9 (2): 125–139.

Johnson, V. A., K. E. Klockow-McClain, R. A. Peppler, and A. M. Person. 2021. "Tornado climatology and risk perception in central Oklahoma." *Weather Clim. Soc.*, 13 (4): 743–751.

Katsura, J., and H. Conner. 2002. "Destruction mechanism of Oklahoma Tornadoes in 1999." *J. Nat. Disaster Sci.*, 24 (2): 61–71.

Kim, J., J. J. Hatzis, K. Klockow, and P. A. Campbell. 2022. "Building Classification Using Random Forest to Develop a Geodatabase for Probabilistic Hazard Information." *Nat. Hazards Rev.*, 23 (3): 4022014.

Kimms, A., and M. Maiwald. 2018. "Bi-objective safe and resilient urban evacuation planning." *Eur. J. Oper. Res.*, 269 (3): 1122–1136.

Krocak, M. J., J. N. Allan, J. T. Ripberger, C. L. Silva, and H. C. Jenkins-Smith. 2021. "An Analysis of Tornado Warning Reception and Response across Time: Leveraging Respondents' Confidence and a Nocturnal Tornado Climatology." *Weather Forecast.*, 36 (5): 1649–1660.

Long, L. N., and H. Weiss. 1999. “The velocity dependence of aerodynamic drag: A primer for mathematicians.” *Am. Math. Mon.*, 106 (2): 127–135.

Mann, H. B. 1945. “Nonparametric tests against trend.” *Econometrica*, 13(3). 245–259.

Mann, H. B., and D. R. Whitney. 1947. “On a test of whether one of two random variables is stochastically larger than the other.” *Ann. Math. Stat.*, 18(1), 50–60.

Manson, S., J. Schroeder, D. Van Riper, T. Kugler, and S. Ruggles. 2021. “IPUMS National Historical Geographic Information System: Version 16.0.” IPUMS National Historical Geographic Information System. Accessed January 15, 2021. http://doi.org/10.18128/D050.V16.0

Mason, L. R., K. N. Ellis, B. Winchester, and S. Schexnayder. 2018. “Tornado warnings at night: Who gets the message?” *Weather Clim. Soc.*, 10 (3): 561–568.

McDonald, J. R., and K. C. Mehta. 2006. “A recommendation for an Enhanced Fujita scale (EF-Scale)”. Accessed May 22, 2022. https://www.depts.ttu.edu/nwi/Pubs/EnhancedFujitaScale/EFScale.pdf

Merrell, D., K. Simmons, and D. Sutter. 2002. “Taking Shelter : Estimating the Safety Benefits of Tornado Safe Rooms.” *Weather Forecast.*, 17 (3): 619–625.

Moore, T. W., and T. A. DeBoer. 2019. “A review and analysis of possible changes to the climatology of tornadoes in the United States.” *Prog. Phys. Geogr. Earth Environ.*, 43 (3): 365–390.

Mostafizi, A. 2016. “Agent-based tsunami evacuation model: life safety and network resilience.” Thesis. Oregon State University. https://ir.library.oregonstate.edu/concern/graduate_thesis_or_dissertations/bv73c493x.

Mostafizi, A., H. Wang, D. Cox, L. A. Cramer, and S. Dong. 2017. “Agent-based tsunami evacuation modeling of unplanned network disruptions for evidence-driven resource allocation and retrofitting strategies.” *Nat. Hazards*, 88: 1347–1372.

Mostafizi, A., H. Wang, D. Cox, and S. Dong. 2019. “An agent-based vertical evacuation model for a near-field tsunami: Choice behavior, logical shelter locations, and life safety.” *Int. J. Disaster Risk Reduct.*, 34: 467–479.

Mostafizi, A., H. Wang, S. Dong, and D. Cox. 2018. "An Agent-Based Model of Vertical Tsunami Evacuation Behavior and Shelter Locations: A Multi-Criteria Decision-Making Problem.", presented at Transportation Research Board 97th Annual Meeting, 2018. https://trid.trb.org/view/1497205.

Nixon, C. J., and J. T. Allen. 2021. “Anticipating Deviant Tornado Motion using a Simple Hodograph Technique.” *Weather Forecast.*, 36 (1): 219–235.

National Weather Service. 1999. “The Great Plains tornado outbreak of May 3-4, 1999.” Accessed May 22, 2022. https://www.weather.gov/oun/events-19990503 .

National Weather Service. 2020a. “Norman, Oklahoma Tornadoes (1890 - present).” Accessed April 27, 2022. https://www.weather.gov/oun/tornadodata-city-ok-norman.

National Weather Service. 2020b. “Moore, Oklahoma Tornadoes (1890 - present).” Accessed April 27, 2022. view-source:https://www.weather.gov/oun/tornadodata-city-ok-moore.

Ono, Y. 2002. “Risk factors for death in the 8 April 1998 Alabama tornadoes”. Accessed: Feb 22, 2022. https://hazards.colorado.edu/uploads/basicpage/QR%20145.pdf.

Pan, X., C. S. Han, K. Dauber, and K. H. Law. 2007. “A multi-agent based framework for the simulation of human and social behaviors during emergency evacuations.” *AI Soc*, 22 (2): 113–132.

Paulikas, M. J., and T. W. Schmidlin. 2017. “US tornado fatalities in motor vehicles (1991--2015).” *Nat. Hazards*, 87 (1): 121–143.

Paulikas, M. J., T. W. Schmidlin, and T. P. Marshall. 2016. “The stability of passenger vehicles at tornado wind intensities of the (Enhanced) fujita scale.” *Weather Clim. Soc.*, 8 (1): 85–91.

Prevatt, D. O., J. W. van de Lindt, E. W. Back, A. J. Graettinger, S. Pei, W. Coulbourne, R. Gupta, D. James, and D. Agdas. 2012. “Making the case for improved structural design: Tornado outbreaks of 2011.” *Leadersh. Manag. Eng.*, 12 (4): 254–270.

Railsback, S. F., S. L. Lytinen, and S. K. Jackson. 2006. “Agent-based simulation platforms: Review and development recommendations.” *Simulation*, 82 (9): 609–623.

Ramsdell, J. V, J. P. Rishel, and A. J. Buslik. 2007. "Tornado climatology of the contiguous United States.". Accessed May 22, 2022. https://www.nrc.gov/reading-rm/doc-collections/nuregs/contract/cr4461/index.html

Ripberger, J., M. Krocak, C. Silva, and H. Jenkins-Smith. 2020a. “WX20. V2.” Harvard Dataverse. Accessed: Oct. 15, 2021. https://doi.org/10.7910/DVN/EWOCUA

Ripberger, J., C. Silva, and H. Jenkins-Smith. 2020b. “WX17. V1.” Harvard Dataverse. Accessed October 15, 2020. https://doi.org/10.7910/DVN/GSTYK4

Ripberger, J., C. Silva, and H. Jenkins-Smith. 2020c. “WX18. V1.” Harvard Dataverse. Accessed October 15, 2020. https://doi.org/10.7910/DVN/RHT4ON

Ripberger, J., C. Silva, and H. Jenkins-Smith. 2020d. “WX19. V1.” Harvard Dataverse. Accessed October 15, 2020. https://doi.org/10.7910/DVN/MLCJEW

Ripberger, J., M. Krocak, C. Silva, and H. Jenkins-Smith. 2021. “WX21. V1.” Harvard Dataverse. Accessed: May. 15, 2022. https://doi.org/10.7910/DVN/QYZLSO

Ripberger, J. T., M. J. Krocak, W. W. Wehde, J. N. Allan, C. Silva, and H. Jenkins-Smith. 2019. "Measuring tornado warning reception, comprehension, and response in the United States." *Weather Clim. Soc.*, 11 (4): 863–880.

Ripberger, J. T., C. L. Silva, H. C. Jenkins-Smith, and M. James. 2015. "The influence of consequence-based messages on public responses to tornado warnings." *Bull. Am. Meteorol. Soc.*, 96 (4): 577–590.

Schmidlin, T. 1997. "Closet, car, or ditch? The mobile home dilemma during a tornado." *Nat. Hazards Observer*, 22 (2): 1–3.

Schmidlin, T., B. Hammer, P. King, Y. Ono, L. Scott Miller, and G. Thumann. 2002. "Unsafe at any (wind) speed? Testing the stability of motor vehicles in severe winds." *Bull. Am. Meteorol. Soc.*, 83 (12): 1821–1830.

Schmidlin, T. W. 2009. "Human fatalities from wind-related tree failures in the United States, 1995–2007." *Nat. Hazards*, 50 (1): 13–25.

Schmidlin, T. W., B. O. Hammer, Y. Ono, and P. S. King. 2009. "Tornado shelter-seeking behavior and tornado shelter options among mobile home residents in the United States." *Nat. Hazards*, 48 (2): 191–201.

Schultz, D. M., E. C. Gruntfest, M. H. Hayden, C. C. Benight, S. Drobot, and L. R. Barnes. 2010. "Decision making by Austin, Texas, residents in hypothetical tornado scenarios." *Weather Clim. Soc.*, 2 (3): 249–254.

Sherman-Morris, K. 2010. "Tornado warning dissemination and response at a university campus." *Nat. Hazards*, 52 (3): 623–638.

Simmons, K. M., and D. Sutter. 2007. "Tornado shelters and the manufactured home parks market." *Nat. Hazards*, 43 (3): 365–378.

Simmons, K. M., and D. Sutter. 2008. “Tornado Warnings, Lead Times, and Tornado Casualties: An Empirical Investigation.” *Weather Forecast.*, 23 (2): 246–258.

Simmons, K. M., and D. Sutter. 2009. “False alarms, tornado warnings, and tornado casualties.” *Weather Clim. Soc.*, 1 (1): 38–53.

Snow, J. T., A. L. Wyatt, A. K. McCarthy, and E. K. Bishop. 1995. “Fallout of debris from tornadic thunderstorms: A historical perspective and two examples from VORTEX.” *Bull. Am. Meteorol. Soc.*, 76 (10): 1777–1790.

Sorensen, J. H. 2000. “Hazard warning systems: Review of 20 years of progress.” *Nat. Hazards Rev.*, 1 (2): 119–125.

Storm Prediction Center. 2021. “SVRGIS.” Accessed May 15, 2022. https://www.spc.noaa.gov/gis/svrgis/

Speheger, D. A., C. A. Doswell, and G. J. Stumpf. 2002. “The tornadoes of 3 May 1999: Event verification in central Oklahoma and related issues.” *Weather Forecast.*, 17 (3): 362–381.

Strader, S. M., A. M. Haberlie, and A. G. Loitz. 2021. “Assessment of NWS county warning area tornado risk, exposure, and vulnerability.” *Weather Clim. Soc.*, 13 (2): 189–209.

Suckling, P. W., and W. S. Ashley. 2006. “Spatial and temporal characteristics of tornado path direction.” *Professional Geographer*, 58 (1): 20–38.

Sutter, D., and K. M. Simmons. 2010. “Tornado fatalities and mobile homes in the United States.” *Nat. Hazards*, 53 (1): 125–137.

Thiele, J. C., W. Kurth, and V. Grimm. 2012. “Agent-based modelling: Tools for linking netlogo and r.” *Journal of Artificial Societies and Social Simulation*, 15 (3): 8.

U.S. Census Bureau. 2010. “TIGER/Line Shapefiles.” Accessed: October 15, 2020. https://www.census.gov/geographies/mapping-files/time-series/geo/tiger-line-file.html

U.S. Census Bureau. 2019. “American Community Survey 1-Year Estimates.” Accessed October 15, 2020. https://www.census.gov/data/developers/data-sets/acs-1year/2019.html

Wang, H., A. Mostafizi, L. A. Cramer, D. Cox, and H. Park. 2016. “An agent-based model of a multimodal near-field tsunami evacuation: Decision-making and life safety.” *Transp. Res. Part C Emerg. Technol.*, 64: 86–100.

Watts, J. 2018. “CHIME ABM Hurricane Evacuation Model (Version 1.2.0).” *CoMSES Computational Model Library*. Accessed August 27, 2019. https://www.comses.net/codebases/5504/releases/1.2.0/.

Wilensky, U. 1999. “NetLogo. V6.1.1". Accessed: Aug 27, 2019. https://ccl.northwestern.edu/netlogo/.

Wolshon, B. 2001. “‘One-way-out’: contraflow freeway operation for hurricane evacuation.” *Nat. Hazards Rev.*, 2 (3): 105–112.

Wurman, J., K. Kosiba, P. Robinson, and T. Marshall. 2014. “The role of multiple-vortex tornado structure in causing storm researcher fatalities.” *Bull. Am. Meteorol. Soc.*, 95 (1): 31–45.

Zhang, Z., K. Spansel, and B. Wolshon. 2014. “Effect of phased evacuations in megaregion highway networks.” *Transp. Res. Rec.*, 2459 (1): 101–109.

Zockaie, A., H. Mahmassani, M. Saberi, and Ö. Verbas. 2014. “Dynamics of urban network traffic flow during a large-scale evacuation.” *Transp. Res. Rec.*, 2422 (1).

Tables

Table 1. Key variables for resident agents and their implementation in TWISTER ABM.

Variables	Type	Definition	Notes
age	static	Resident's age group	Weighted random draw based on 2019 Norman population
ethnicity	static	Resident's ethnic group	Weighted random draw based on 2019 Norman population
race	static	Resident's race	Weighted random draw based on 2019 Norman population
speed	dynamic	Resident's current speed (patches/tick)	Varies when resident is on foot or in car
dead?	dynamic	Resident's death status	Binary flag (dead = true, alive = false)
evacuated?	dynamic	Resident's evacuation status	Binary flag (evacuated = true, not evacuated = false)
max_ef	dynamic	Maximum wind speed experienced by resident	Wind speed is reported as an EF level
warn_rcv	static	Probability that the resident will recieve a warning	Random normal draw based on WX Survey data
warn_comp	static	Probability that the resident will understand a warning	Random normal draw based on WX Survey data
warn_resp	static	Probability that the resident will respond to a warning	Random normal draw based on WX Survey data
risk_life	static	Probability that resident will switch routes or destinations if passing close to a tornado	Random normal draw with a mean of 50% and a standard deviation of 10%
milltime	static	Milling time before the resident makes a decision (in seconds)	Random normal draw from Durage et al. (2014) survey data
action	dynamic	Protective action taken by the agent (e.g., Do Nothing, Evacuate) (string)	Weighted random draw from WX Survey data
evac_start	dynamic	Time when the resident started moving to shelter or evacuation point (in minutes)	
evac_end	dynamic	Time when the resident arrived at their destination (in minutes)	
evac_dur	dynamic	Duration of evacuation (in minutes)	
evac_dist	dynamic	Distance traveled to destination (in meters)	
location	dynamic	The resident's current location type	Location types include car, outside, refuge, etc.

Table 2. Key variables for tornado agents and their implementation in TWISTER ABM.

Variables	Type	Definition	Notes
ef0_radius	static	Radius of EF0 wind field (in patches)	From Ramsdell and Rishel (2007)
ef1_radius	static	Radius of EF1 wind field (in patches)	From Ramsdell and Rishel (2007)
ef2_radius	static	Radius of EF2 wind field (in patches)	From Ramsdell and Rishel (2007)
ef3_radius	static	Radius of EF3 wind field (in patches)	From Ramsdell and Rishel (2007)
ef4_radius	static	Radius of EF4 wind field (in patches)	From Ramsdell and Rishel (2007)
ef5_radius	static	Radius of EF5 wind field (in patches)	From Ramsdell and Rishel (2007)
speed	static	Speed of tornado (in patches/tick)	
path_len	dynamic	Length of tornado path (in km)	

Table 3. Standard parameter settings for TWISTER ABM.

Parameter	Value
Scenario	Scenario 1 (everyone who responds to the warning seeks refuge, seeks shelter, or evacuates)
Monte Carlo Simulations	20
Time	1700 LT (on a weekday)
Time Delay for Additional Background Traffic Agents	10 s
# of Agents	4000
% of Residences with Shelter	10%
# of Public Shelters	20
Tornado Intensity	EF5
Tornado Width	1.6 km
Tornado Speed	45.1 km/h
Tornado Lead Time	15 min

Table 4. Parameter settings and the corresponding values used in each sensitivity analysis.

Sensitivity Analysis	Parameter	Values
Time of Day	*Time*	0100 LT, 0500 LT, 0900 LT, 1200 LT, 1700LT, 2100 LT
Tornado Intensity	*Tornado Intensity*	EF0, EF1, EF2, EF3, EF4, EF5
	Tornado Width	49.8 m, 154.5 m, 318.2 m, 600.8 m, 872.3 m, 1414.6 m
Tornado Lead Time	*Tornado Lead Time*	0 min, 5 min, 15 min, 30 min, 45 min, 60 min
Residential Shelter Availability (% of total Residential Buildings)	*% of Residences with Shelter*	1%, 5%, 10%, 20%, 40%, 80%
Public Shelter Availability (# of Buildings)	*# of Public Shelters*	5, 20, 50, 200, 1000, 1800

Source: Storm Prediction Center's (SPC) SVRGIS (SPC 2021).
Mean tornado widths are for the period of 1995 to 2020. For the tornado intensity sensitivity test the tornado intensity and tornado width parameters vary together simultaneously.

Figure Captions

Fig. 1. The interface of the tornado warning-induced shelter, travel and evacuation response agent-based model (TWISTER ABM) in NetLogo.

Note: The left panel contains the adjustable parameters for the simulations, including parameters related to the number of residential and public shelters, parameters for the GM car-following model, pedestrian speed, tornado intensity, width, and speed, and whether background traffic is included in the simulation. A visualization of the simulation as it unfolds can be seen in the center panel. The damage path of the tornado is represented by grey shading with darker color cells experiencing higher wind speeds. A black tornado icon represents the current position of the center of the tornado. Buildings are represented as squares with small squares corresponding to buildings that are not FEMA-rated shelters (refuges) and large squares corresponding to FEMA-rated shelters (shelters). Throughout the shape representing the agents changes as their status changes. Small x's represent fatalities. Flags represent agents who have successfully completed their protective action. Circles represent agents who are monitoring the situaiton. Triangles represent agents who are seeking refuge (small triangles) or seeking shelter (large triangles). Arrow heads represent agents who are evacuating. The right panel shows simulation results including the total number of fatalities by location, the percentage of agents evacuated by protective action type, and the distribution of protective action completion times.

Fig. 2. Flowchart for typical TWISTER ABM model run.

Note: Model processes are the light grey rounded rectangles. Decisions are grey diamonds and the protective action types are the dark grey rounded rectangles.

Fig. 3. Study area and location within Norman, Oklahoma.

Note: In panel (a), building points that are circles are buildings that do not have FEMA-rated shelters (refuges) while ones that are triangles are buildings with FEMA-rated shelters (shelters). Evacuation points are represented as squares and the local roads are the black lines. In panel (b), we see the city of Norman, Oklahoma (shaded light grey) as well as the neighboring communities (with Moore shaded in grey) with all primary and secondary roads as black lines. The location of the study area within Norman is defined by the solid outline. (All map data is from the U.S. Census Bureau (2010)).

Fig. 4. Snapshots of a TWISTER ABM simulation

Note: Each run begins with the issuance of a tornado warning (a) and ends with the tornado passing out of the study area and dissipating (f). Panel a shows the initial distribution of the agents (dots) based on the American Time Use Survey data for the hour of the simulation (1700 LT in this case). Agents are distributed to building locations, points outdoors, or points along the road network. By 15 minutes (b and c), the tornado has formed outside the study area and many agents have successfully completed their protective action (diamonds). By 24 minutes (c and d) the tornado has advanced into the study area (its path is marked by the grey shaded cells with the darker colors indicating stronger winds) and caused the first fatalities (x’s). The model run ends with the tornado passing out of the study area and dissipating (f).

Fig. 5. Fatality rate for observed and simulated significant and violent tornadoes.

Note: Fatality rate is in fatalities per 1000 residents living in the path of the tornado. Observed values are for tornadoes hitting within 100 km of Oklahoma during the 1995 – 2020 time period.

Fig. 6. Travel time comparison between TWISTER ABM and Google estimated travel times.

Note: Comparisons are for 0200 LT (a) and 1700 LT (b). Linear trend line with the regression equation and Pearson’s correlation coefficient are added for reference. Estimated travel times are calculated using the mapsapi R package (Dorman 2022) and the Google Directions API (Google 2022) with the best guess traffic model.

Fig. 7. Model sensitivity to tornado intensity and width.

Note: Sensitivity is measured by fatality rate (‰) (a), mean trip duration for trips to refuges, shelters, or evacuation points (minutes) (b), and percentage of agents taking protective action (c). Bold lines represent the median values. Boxes show the interquartile range (25^{th} to 75^{th} percentiles) with whiskers extending to 1.5 times the interquartile range.

Fig. 8. Model sensitivity to time of day.

Note: All panels are as in Fig. 7.

Fig. 9. Model sensitivity to lead time.

Note: All panels are as in Fig. 7.

Fig. 10. Model sensitivity to residential shelter availability.

Note: All panels are as in Fig. 7.

Fig. 11. Model sensitivity to public shelter availability.

Note: All panels are as in Fig. 7.

Fig. 12. Sensitivity of model output to eight different protective action scenarios

Note: Measures include fatality rate (‰) (a), percentage of agents taking (triangles) and completing (inverted triangles) protective action (b), mean completion time (time required to reach the protective action destination) (minutes) (c), and the percentage of agents completing their protective action within 15 minutes out of all agents (triangles) and out of those that completed their protective action (inverted triangles) (d). Bold lines represent the median values. Boxes show the interquartile range (25th to 75th percentiles) with whiskers extending to 1.5 times the interquartile range. Scenarios are as follows: (1) everyone who responds to the warning (responders) seeks refuge, seeks shelter, or evacuates, (2) all responders evacuate, (3), all responders shelter-in-place, (4) all responders seek shelter only, (5) all agents evacuate, (6) all agents shelter-in-place, (7) all agents seek shelter, (8) all agents do nothing.

Figure1

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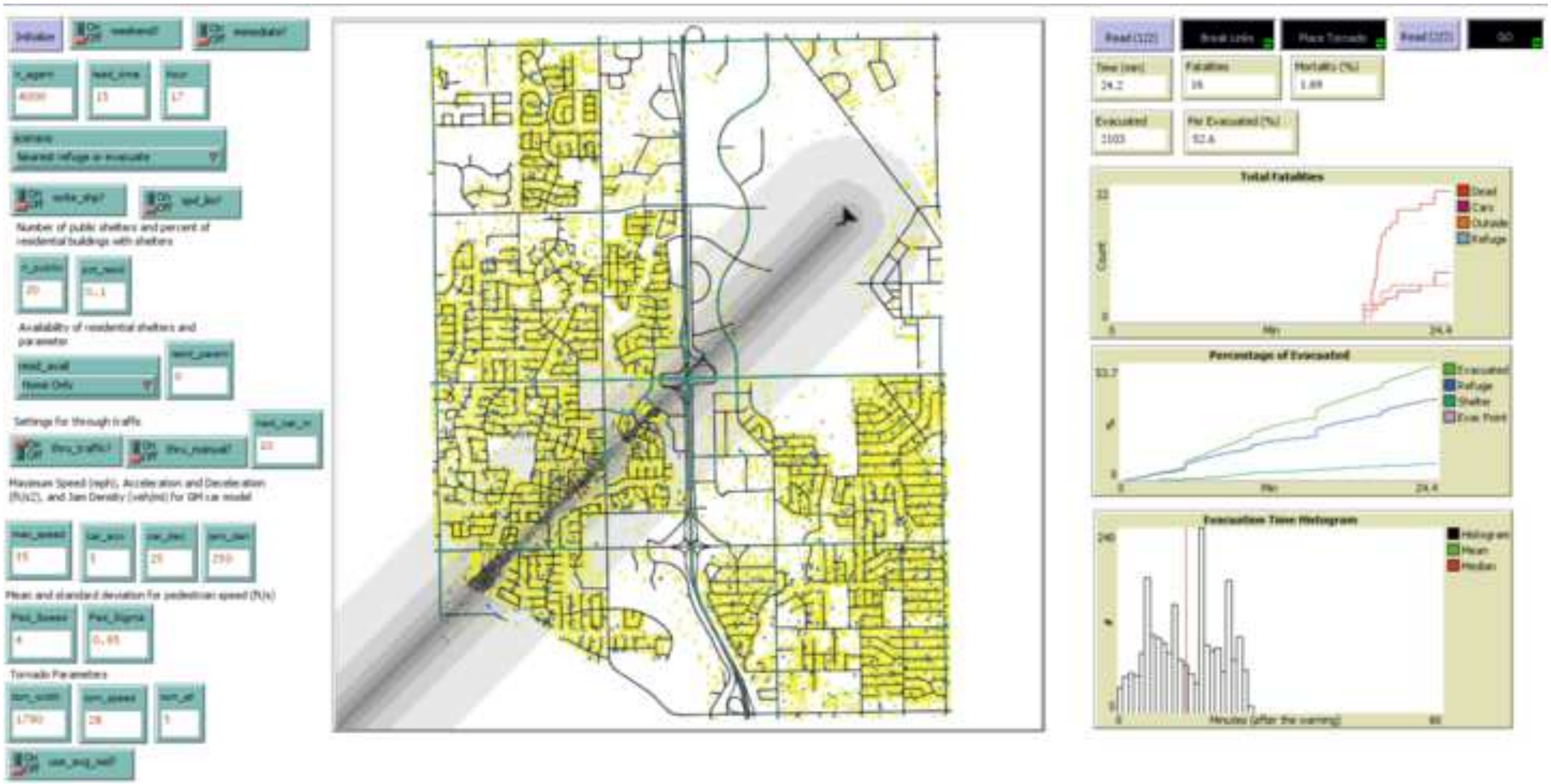

Figure2

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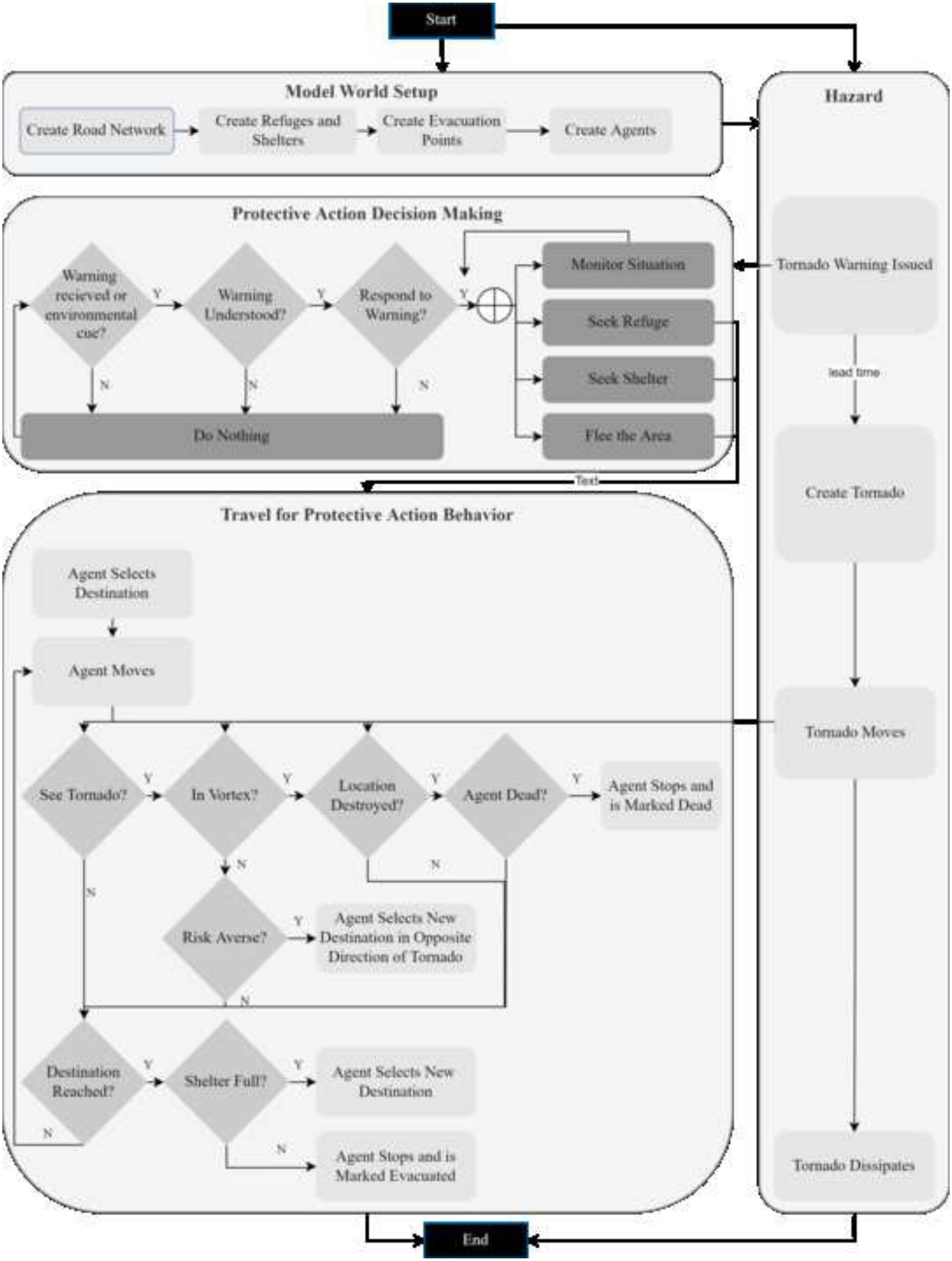

Figure3

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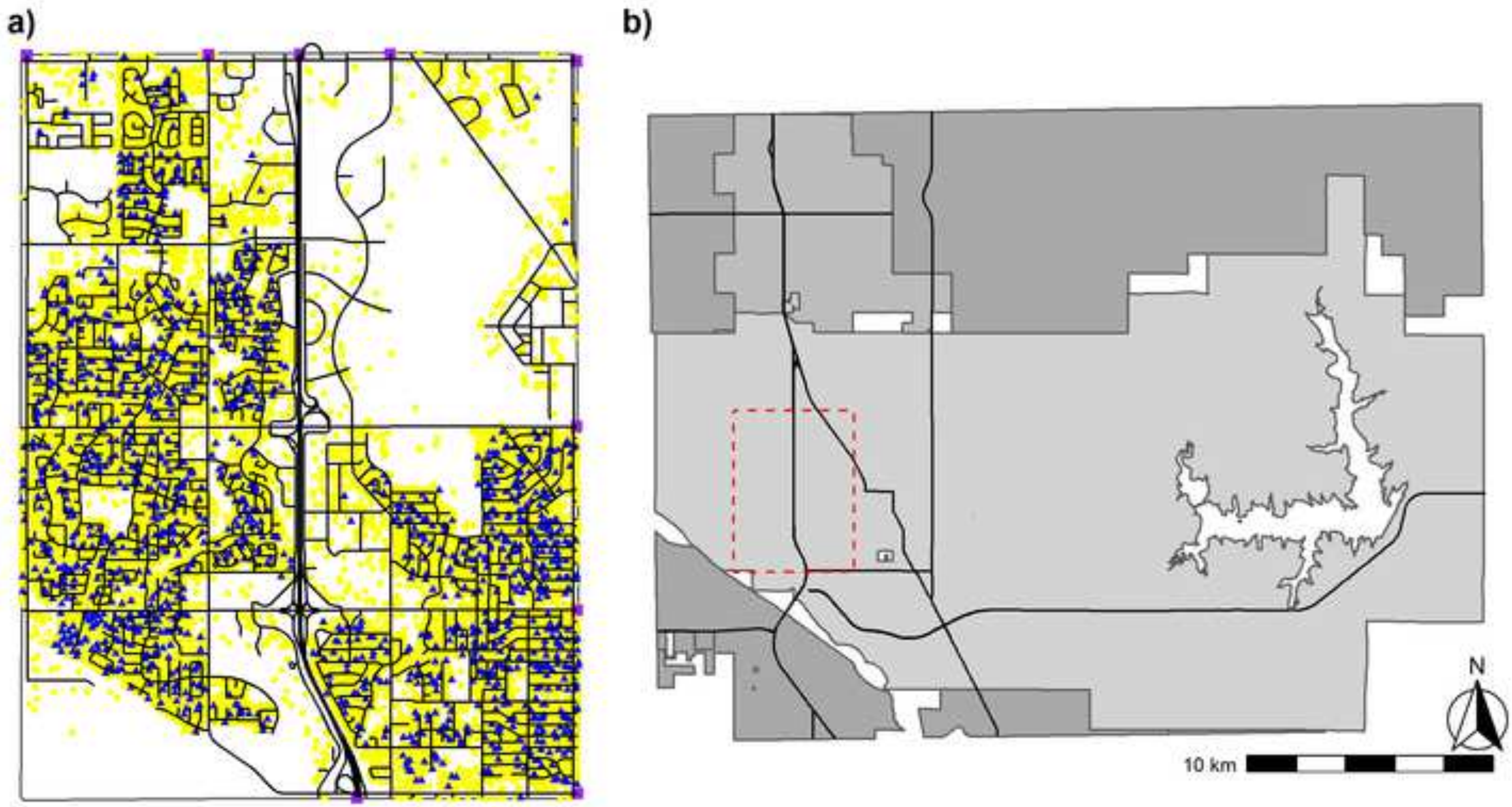

Figure4

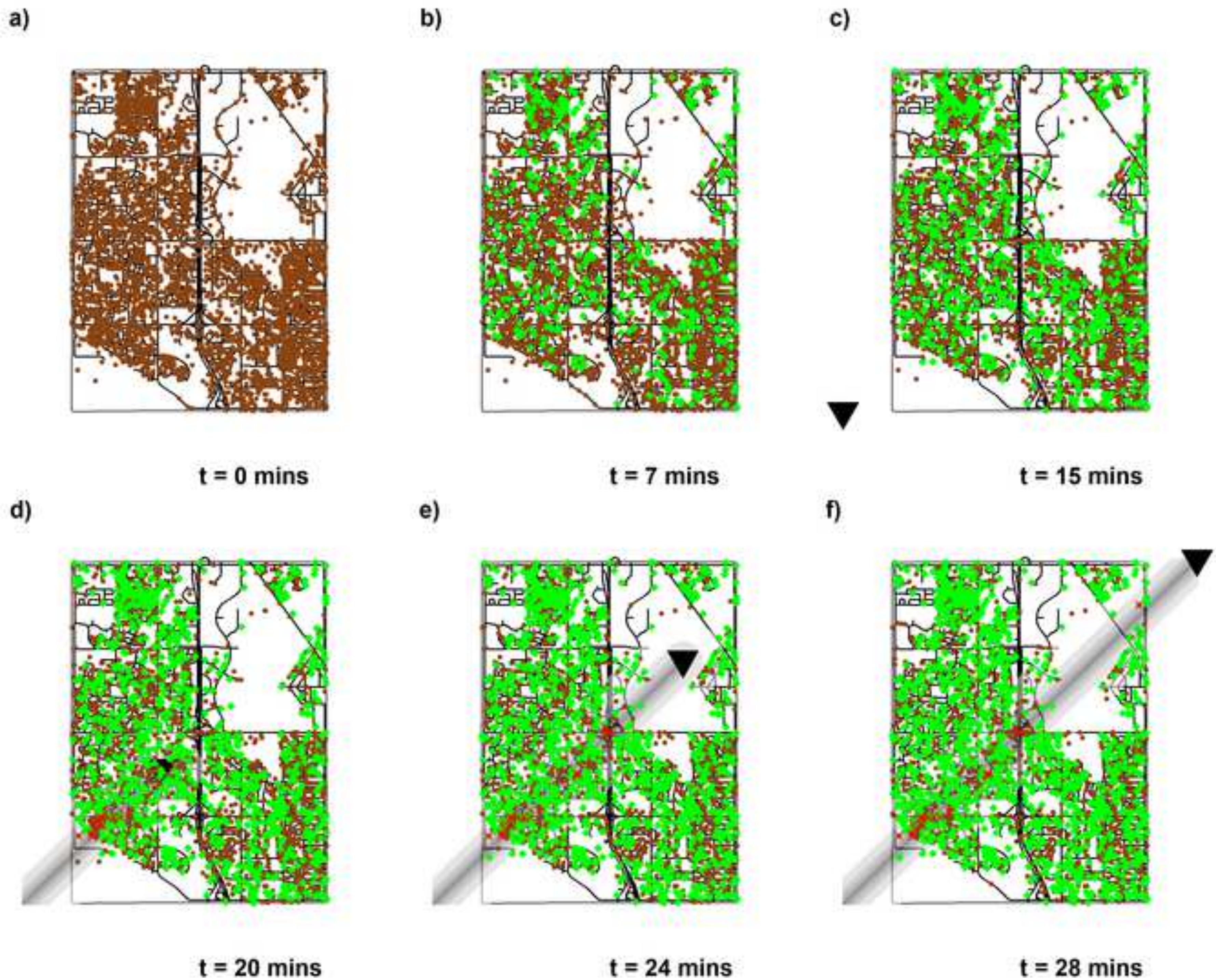

Figure5 Click here to access/download;Figure;Figure5.tiff

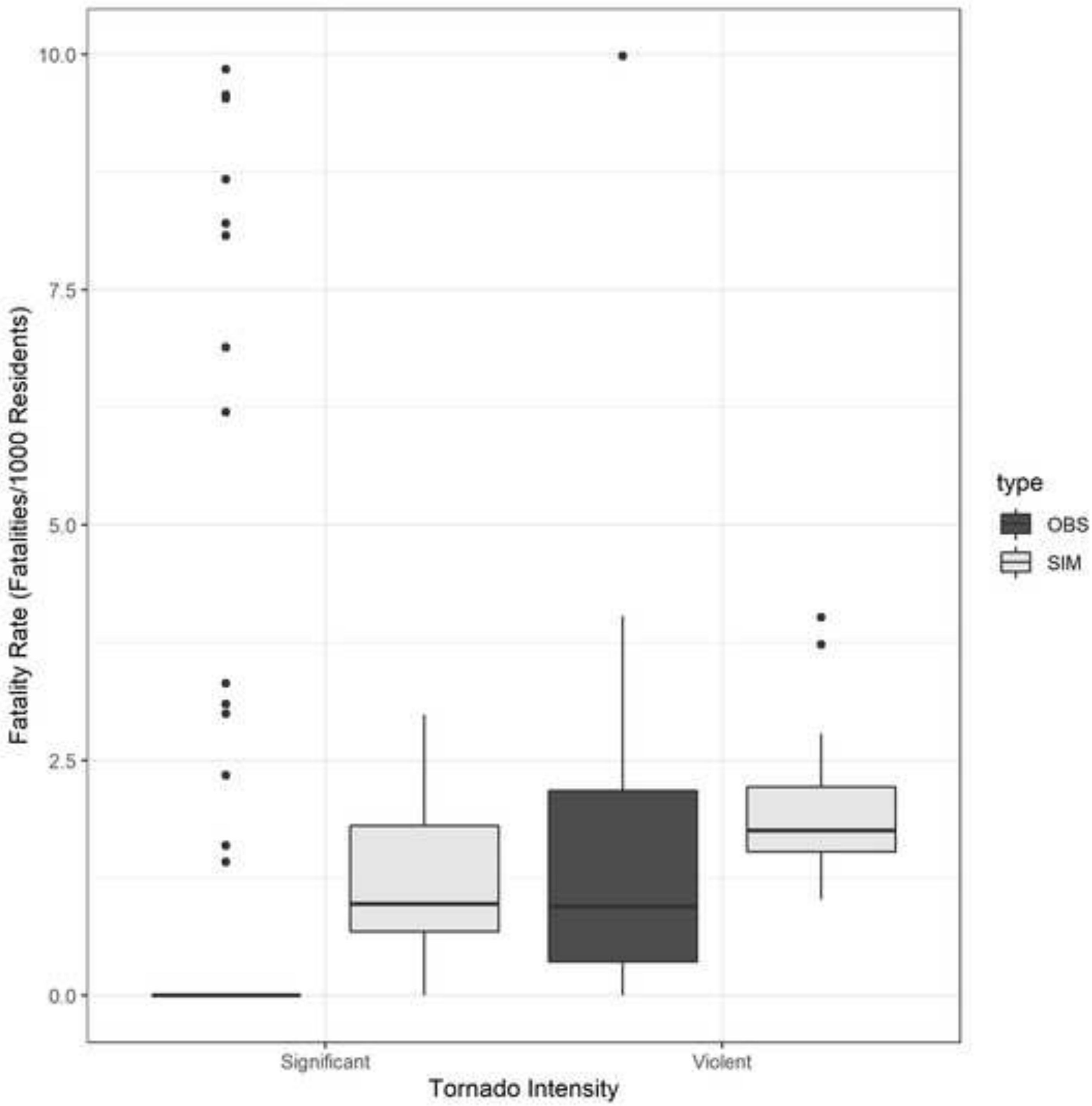

Figure6

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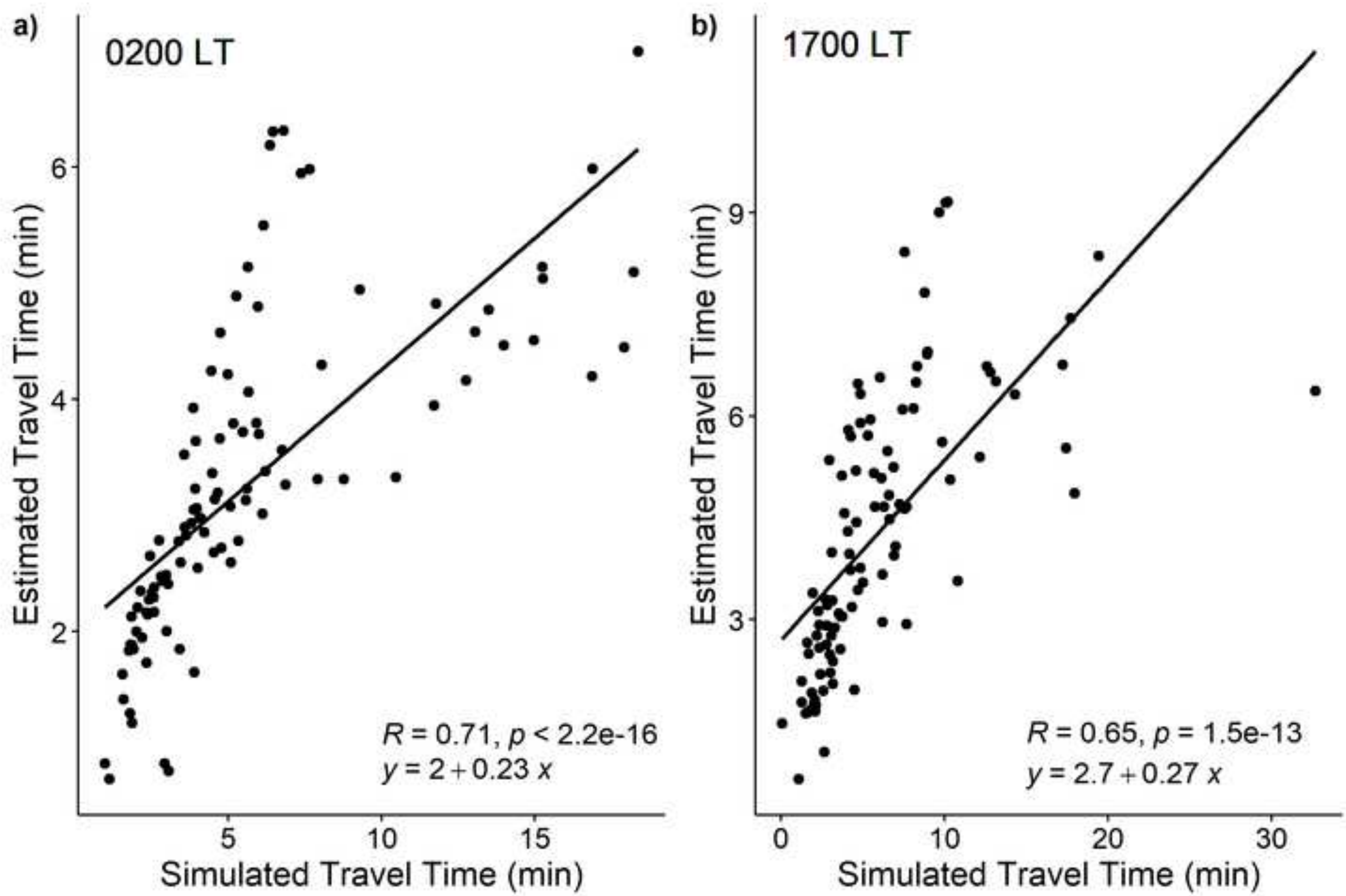


Figure7

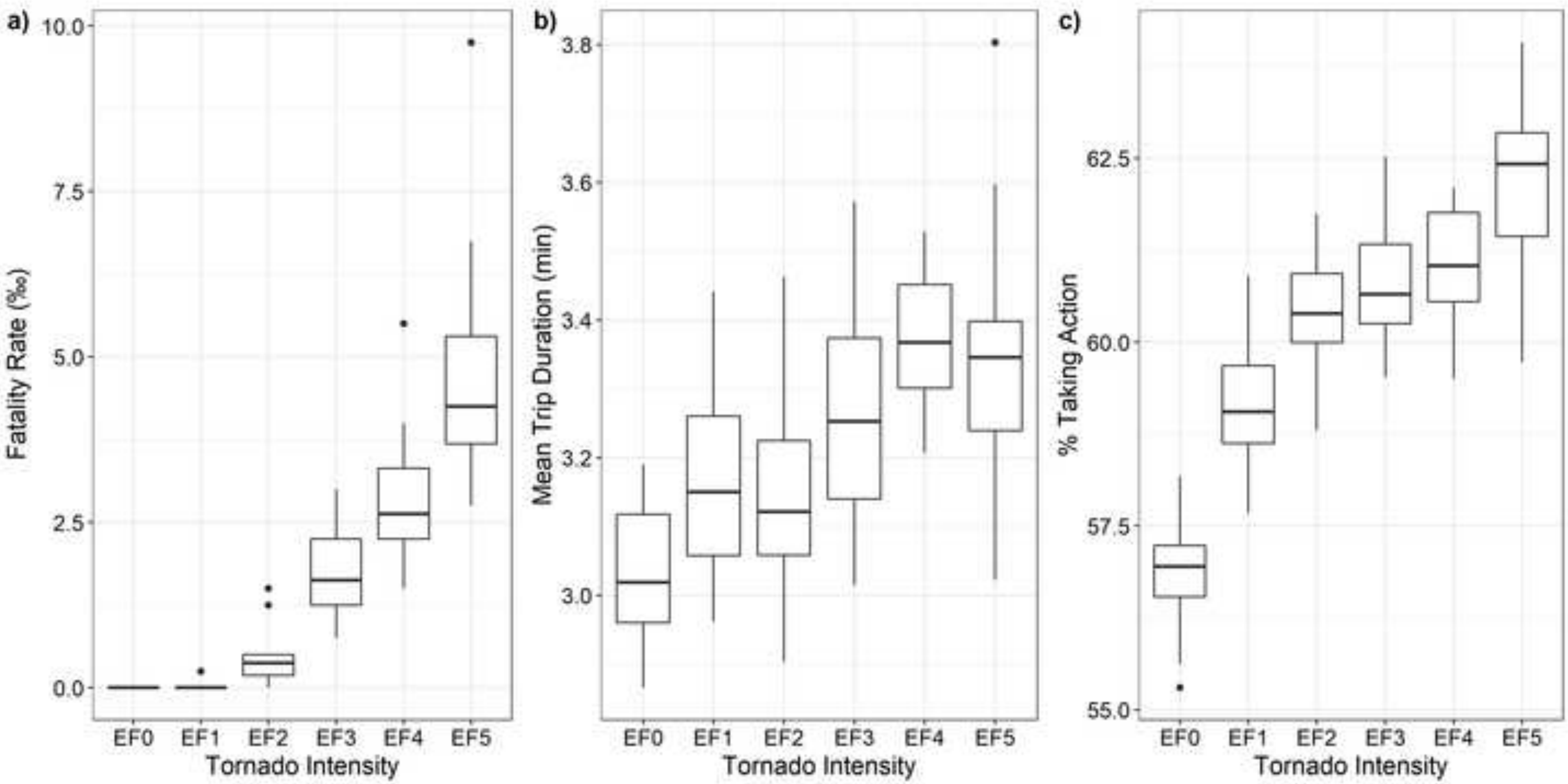

a)
b)
c)
Fatality Rate (‰)
Mean Trip Duration (min)
% Taking Action
Tornado Intensity
EF0
EF1
EF2
EF3
EF4
EF5
10.0
7.5
5.0
2.5
0.0
3.8
3.6
3.4
3.2
3.0
62.5
60.0
57.5
55.0

Figure8

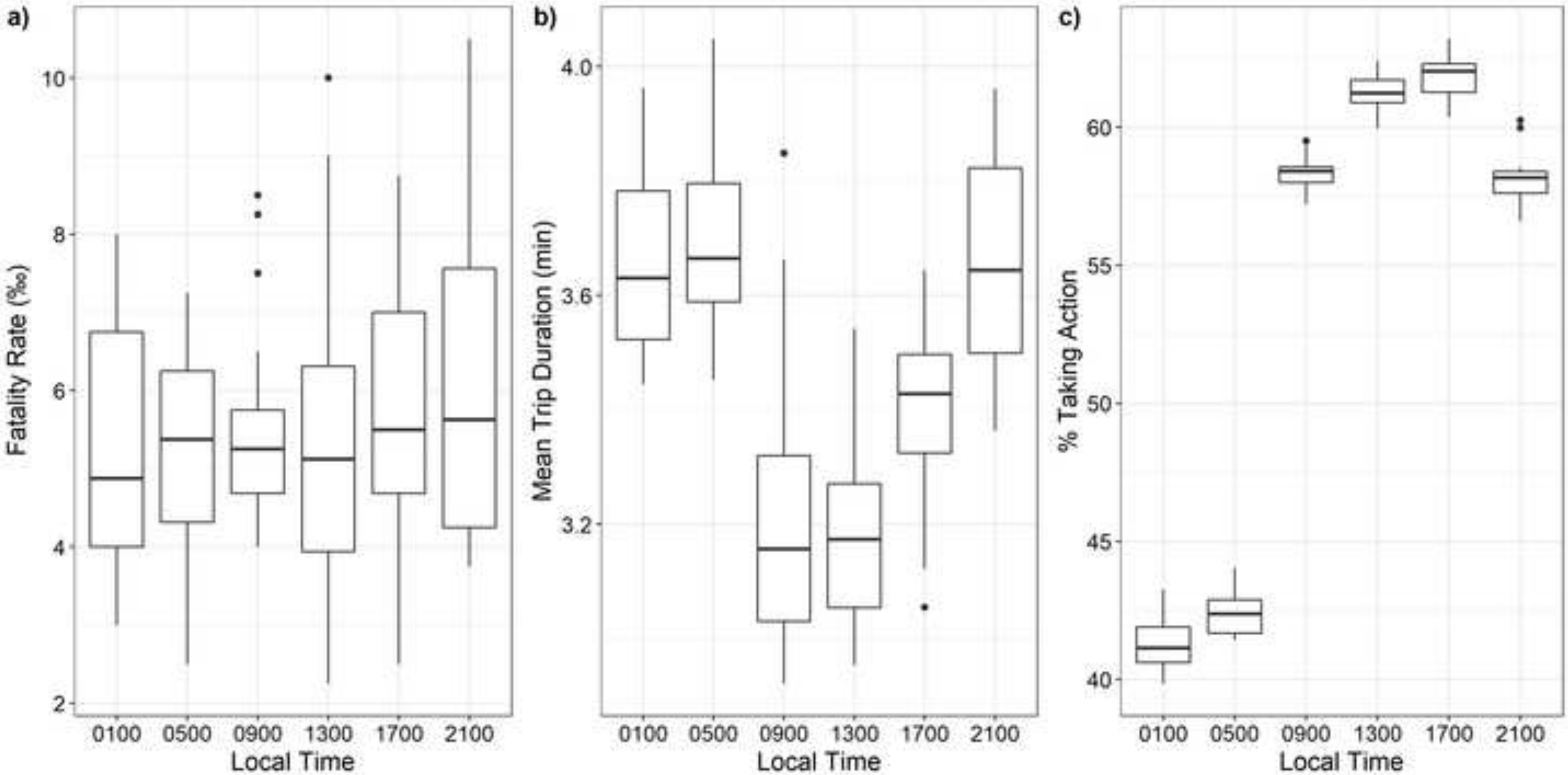

a)
b)
c)
Fatality Rate (‰)
Mean Trip Duration (min)
% Taking Action
10
8
6
4
2
4.0
3.6
3.2
60
55
50
45
40
0100
0500
0900
1300
1700
2100
Local Time
Local Time
Local Time

Figure9

Click here to access/download;Figure;Figure9.tiff

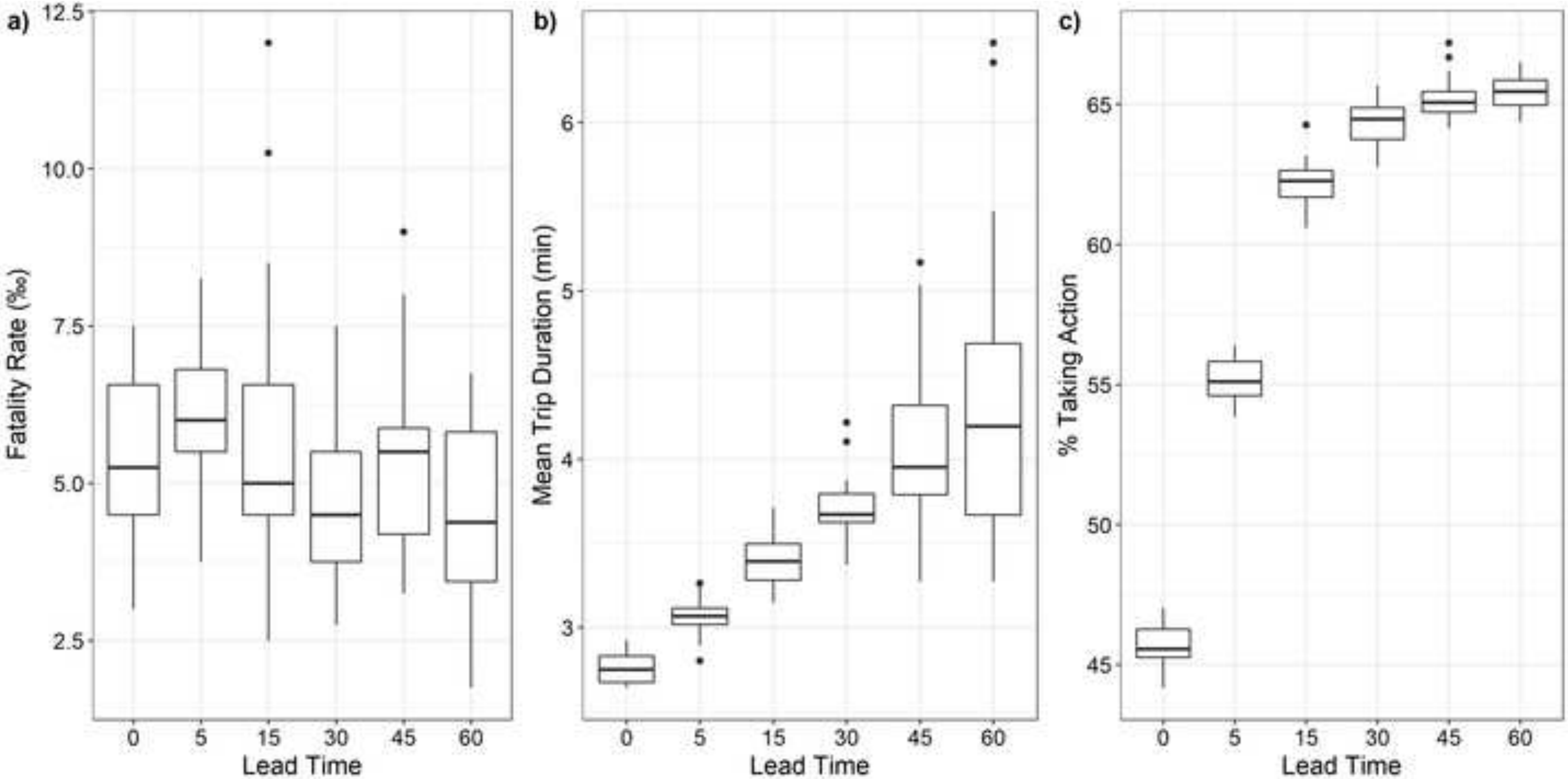
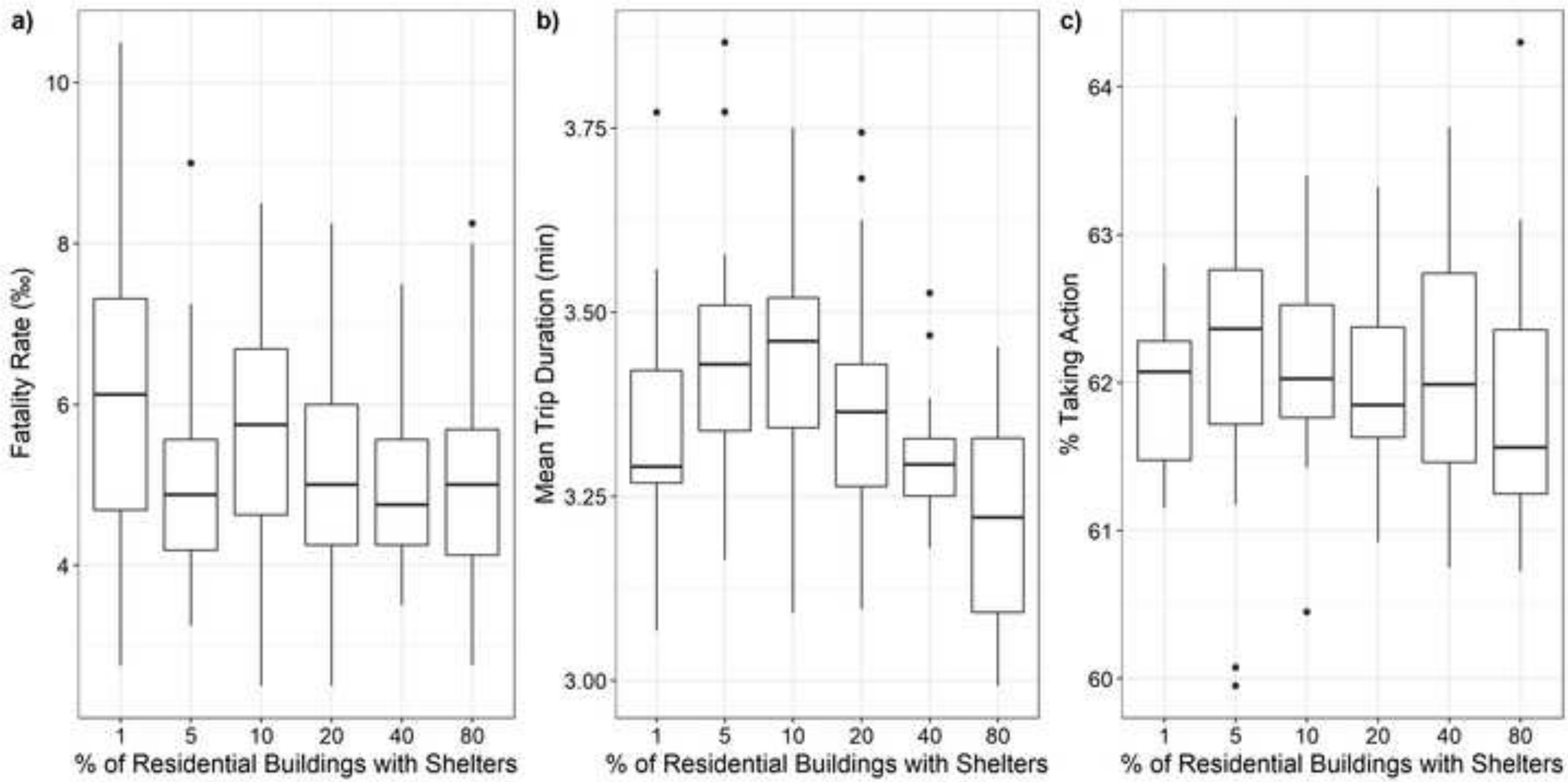


Figure10



a)
Fatality Rate (‰)
10
8
6
4
1
5
10
20
40
80
% of Residential Buildings with Shelters
b)
Mean Trip Duration (min)
3.75
3.50
3.25
3.00
1
5
10
20
40
80
% of Residential Buildings with Shelters
c)
% Taking Action
64
63
62
61
60
1
5
10
20
40
80
% of Residential Buildings with Shelters

Figure11

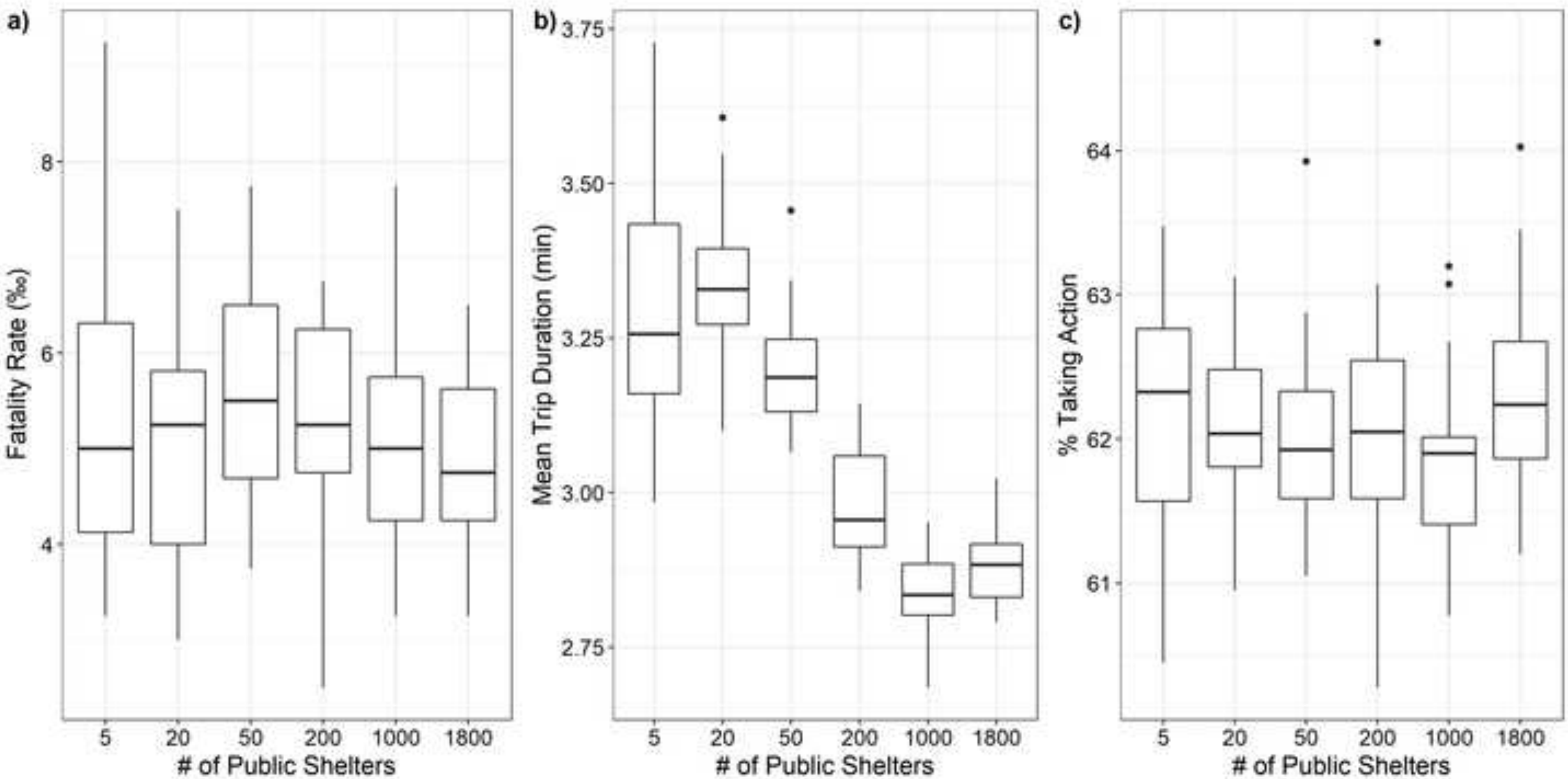

a)
b)
c)
Fatality Rate (‰)
8
6
4
Mean Trip Duration (min)
3.75
3.50
3.25
3.00
2.75
% Taking Action
64
63
62
61
5
20
50
200
1000
1800
# of Public Shelters

Figure12

Click here to access/download;Figure;Figure12.tiff