HHS Public Access
Author manuscript
Auton Agent Multi Agent Syst. Author manuscript; available in PMC 2016 November 29.

Published in final edited form as:
Auton Agent Multi Agent Syst. 2016 November ; 30(6): 1148–1174. doi:10.1007/s10458-016-9331-y.

A comparison of multiple behavior models in a simulation of the aftermath of an improvised nuclear detonation

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Abstract

We describe a large-scale simulation of the aftermath of a hypothetical 10kT improvised nuclear detonation at ground level, near the White House in Washington DC. We take a synthetic information approach, where multiple data sets are combined to construct a synthesized representation of the population of the region with accurate demographics, as well as four infrastructures: transportation, healthcare, communication, and power. In this article, we focus on the model of agents and their behavior, which is represented using the options framework. Six different behavioral options are modeled: household reconstitution, evacuation, healthcare-seeking, worry, shelter-seeking, and aiding & assisting others. Agent decision-making takes into account their health status, information about family members, information about the event, and their local environment. We combine these behavioral options into five different behavior models of increasing complexity and do a number of simulations to compare the models.

Keywords

Social Simulation; Behavior Modeling; Disaster Modeling

1 Introduction

Over the past several years, agent-based modeling has become an increasingly popular methodology in the social sciences [30,17,22]. This has been driven by the understanding that agent-based modeling affords the exploration of the mechanisms that lead to large-scale social changes. The goal is generally to explain some empirically-observed facts or some stylized facts [23]. A stylized fact is an observed regularity such as a power-law degree distribution in various networks.

The general paradigm in this kind of research is to go from the observed macro-conditions to a description of micro-level behaviors or beliefs that are shaped and constrained by these macro-conditions. These micro-level behaviors lead to particular kinds of actions, from which new aggregate-level social phenomena emerge through the interactions between individuals. In other words, the observed macro-conditions do not directly *cause* the observed consequent social phenomena, rather the causal route is via micro-level behaviors and actions and must be explained as such. This is where agent-based modeling can contribute, because it can be used to directly represent and experiment with the micro-level behaviors and actions.

An important question raised by this approach is, which micro-level behaviors and actions are necessary and sufficient to include in the agent-based model? In general, it may be possible to obtain the observed social phenomena through multiple models. The problem is exacerbated when the model is intended to guide policy, for example in disaster response domains, because policy-making requires reasoning about counterfactual scenarios. It is often the case that the disaster that is being planned for has never happened before, at least in the particular locations and circumstances being considered. In such a scenario, the role of a model (agent-based or otherwise) is to provide a forecast of the potential outcomes as an aid to decision-making at the policy level.

Forecasts depend upon representational choices in the model. Disasters are complex systems [5], with feedback loops between individual behaviors and various infrastructures and therefore which behaviors are represented in the model can have a subtle impact on the forecasts generated by the model.

In this work, we present a detailed, large-scale simulation of a particular disaster scenario: the detonation of an improvised nuclear device in Washington DC. This is known as National Planning Scenario 1 (NPS-1). The physical aspects of this scenario have been studied for a long time[1], but only recently has attention turned to the effects of human behavior on outcomes such as casualty and mortality levels [40, e.g.].

Empirical studies of various kinds of disasters have revealed the various kinds of behaviors that people engage in after a disaster occurs, including looking for family members [21], seeking information [36], seeking shelter [24], and more. Studies of NPS-1 have focused only on some of these behaviors, such as the relative benefits of sheltering versus evacuation [15,40,14].

Here we study the question, do other behaviors matter? If we include consideration of other disaster-related behaviors that have been empirically identified, will that change forecasts? If so, does the difference in forecasts matter to policy-making? For example, if modeling additional behaviors only improves the outcome forecasts, perhaps we are justified in leaving them out for worst-case planning. If, on the other hand, modeling additional behaviors leads to non-monotonic impacts on the outcome, it would suggest that we need to be more careful and complete in our models that guide policy-making.

We study five different behavior models, of increasing complexity. The first is a null model where individuals do nothing. This forms our baseline scenario. The next two models are taken from the prior studies and only consider sheltering and evacuation. The fourth model adds healthcare-seeking and worry behaviors, and the fifth model adds household

[1] http://nuclearsecrecy.com/blog/2011/12/30/friday-image-bullseye-on-washington-1953/

reconstitution and aid & assist behaviors (for a total of six behaviors). We show that, as we add more and more behaviors, expected outcomes change non-monotonically. Outcomes improve as we move from the sheltering and evacuation models to the model that includes healthcare-seeking and worry behaviors, but then get worse when we include the final two behaviors.

This paper builds upon an earlier paper which presented the six-behavior model only [33]. The present work substantially revises and extends the earlier work. All the experiments and results presented in this work are new.

The rest of this article is organized as follows. First we describe the scenario in some detail. After that, we describe the synthetic population generation methodology, which is used to generate the agent population used in the simulations. Then we describe the design of the agents, including five different behavioral models of increasing complexity. This is followed by a series of experiments which evaluate the differences due to the behavior models. We end with a discussion of the implications of choosing behavioral models of different levels of complexity for policy planning.

2 Scenario

As part of National Planning Scenario 1, Buddemeier et al. [12] elaborated the unfolding situation in the wake of a hypothetical low yield 10-kT detonation in downtown Washington DC at the intersection of K Street NW and 16th Street NW on May 15th 2006, at 11:15 EDT. Unlike cold-war scenarios with 1 mT or more, this low-yield detonation scenario offers some time and opportunity to respond and to save lives [14,40]. Our work builds on top of this work to understand effects of this detonation in immediate and short terms on infrastructure, people and their interactions. The main difference we assume is that a large fraction of the population will have cellular phones. Several cell phone base stations are expected to cease functioning due to the effects of the explosion, however.

Two kinds of effects of such a detonation are studied, viz. Prompt Effects within first minute of the event and Delayed Effects after the first minute and usually up to several weeks or even years. Immediately after the detonation, a blast crater is formed at the site due to the enormous energy released by the explosion and dust and debris are lifted up in the air as a climbing cloud—for low-yield detonation, it may not gain the characteristic “mushroom” shape. Depending upon weather conditions, the cloud may accelerate up to 5 miles (8 km) high in the atmosphere and in the process may lose the original shape. By this time, the dust and debris in the cloud are mixed up with radioactive particles. As the cloud cools, these particles start falling to the ground, with larger particles closer to the site and finer ones carried away by wind. This is the fallout, which is counted as part of the delayed effects.

Prompt effects are dependent on the factors such as location, time and intensity of the detonation (10 kT in this scenario), and attributes of structures such as buildings and roads. One of the devastating prompt effects, the blast shockwave, damages structures while radially expanding out. Depending upon the observable damage, Buddemeier et al. [12] suggest three damage zones: Severe, Moderate and Light.

The Severe Damage Zone (SDZ) is expected to be approximately 0.5–0.6 miles in radius for this scenario. Within this radius, buildings and structures are not expected to withstand the intensity of the blast shockwave, with exception of only a few solid buildings and underground structures such as subway tunnels. Due to dangerously high levels of radiation, the SDZ is a no-go zone for everyone including responders. Thus likelihood of survival is very low.

Within the Moderate Damage Zone (MDZ), one can see significant damage to buildings and structures. The MDZ starts after the SDZ, stretching up to 1 mile from ground zero. Radiation levels here can cause serious injuries to individuals who are outdoors. Many individuals are expected to sustain serious injuries, due to radiation and other compounded effects of the detonation. Many of these individuals can be saved through early medical assistance. Fig. 1 renders damage zones as concentric circles, with ground-zero as the center, the SDZ as the inner circle and the MDZ as the outer circle.

Beyond the MDZ is the Light Damage Zone (LDZ), up to 3 miles from ground zero. Based upon damage such as shattered window glass, the LDZ may stretch up to 10 miles from ground zero. Radiation exposure in this zone is unlikely to cross lethal levels. Individuals will face minor injuries mostly because of effects of the shockwave and can survive even without immediate medical help.

For our study, the building damage data are shown in Fig. 2, with red, yellow and green colors denoting severe, partial and no damage respectively. The level of radiation protection offered by a building is inversely related to the level of damage it sustains, Thus, severely damaged buildings are less qualified to be considered as shelters and may be dangerous because of structural weaknesses.

Unlike the prompt effects, delayed effects last longer, from hours to days and from weeks to years. These include immediate fallout effects and long-term health hazards. Exposure to fallout may cause individuals within 20 miles from ground zero to show symptoms such as nausea and vomiting, whereas long-term hazards may include development of cancers. Fallout effects are mostly dependent on the weather conditions during and after the time of event affecting its shape and pace. Ultimate effects also depend upon behavior of individuals, for example, some may decide to shelter in buildings whereas others may decide to evacuate. Falling particles start depositing on open sides of buildings and structures and exposure to their radiation can be hazardous depending upon several factors such as construction material, amount of damage, safe sheltering locations and so on. Buddemeier et al. [12] classify the critical fallout region into two zones based on radiation levels. The Dangerous Fallout Zone (DFZ) is defined as having radiation more than 10 Roentgens/hr whereas radiation for the Hot Fallout Zone (HFZ) is between 0.01 R/hr and 10 R/hr. Fallout zones and damage zones overlap causing compounded effects. Over time, both of these zones shrink.

The fallout zones of our study are rendered in Fig. 3, with color gradient indicating average radiation level over three hours from the event, such that darker and lighter regions imply higher and lower radiation levels typically ranging between 1000 R/hr and 0.01 R/hr. During simulation of the first 48 hours, we found that fallout reaches up to 50 miles away from ground zero.

Likelihood of survival in the MDZ is more complicated than in the SDZ and the LDZ. The SDZ situation happens to be too dire to hope for search and rescue whereas in the LDZ individuals can take care of themselves or of each other with little or no medical assistance. However in the MDZ, individuals can survive without much injury when they are not exposed to prompt and fallout effects such shockwave and radiation. The MDZ has higher possibility of saving injured individuals if medical help is promptly reached to them. Responders can venture into the MDZ, but at the same time the state of the infrastructure may not be favorable to conduct search and rescue operations at the desired pace. There is also a risk that relatively healthy individuals will come out of their shelters, motivated by various reasons such as finding family members or lack of information about outside events and expected actions, or misinformation about safety levels of their current place. The behavior of individuals may affect one another resulting into a contagion. Walking outside results in a cumulative exposure to fallout radiation and may deteriorate health significantly depending up on initial health condition, location, radiation levels and so on. The resulting behavior may put additional burden on infrastructure such as congestion to communication with cell towers and to walk on roads. Fig. 4 shows how radiation decays near ground zero over time.

We simulate the population inside a region we call the detailed study area (DSA), which is the area defined by the 0.01 Gy fallout contour[2] at 60 minutes joined with the thermal radiation contour at 2.1 cal/cm^2 bounded by the boundary of the counties neighboring the District of Columbia.

3 Design of the simulation

The design of the simulation has been described in detail elsewhere [7]. We summarize it here for completeness.

The simulation is designed around a synthetic information framework [31]. We built a realistic representation of the population of the region, including demographics, daily activity patterns, and locations [2,11,8]. This is known as a synthetic population. We also built representations of four infrastructures: the cell phone network, the transportation network, the healthcare system, and the power system. Of these, the power system is not expected to regain function in the affected areas during the 48 hours after the event, so it is not dynamically updated in our simulation. Power outage areas are determined at the beginning of the simulation and form part of the initial conditions. The other systems are updated during the simulation. Details of the cell phone network have been presented by Chandan et al. [13], and of the transportation system have been presented by Adiga et al. [3,4]. The healthcare module is described below in section 4.4 and has also been discussed by Lewis et al. [26].

[2]The unit Gray (Gy) expresses absorbed radiation. Roentgen (R) is the unit for exposure in air. It is assumed that 1 R = 0.01 Gy [12].

The scenario affects all individuals present in the detailed study area (DSA) at the time of detonation. This includes area residents, tourists, business travelers, and college students. The health and behavior of an agent depends upon its demographics as well as its location in the immediate aftermath of the disaster, for example, one of the common behaviors in disasters is household reconstitution where a person tries to gather his family members [16,28]. Similarly, if a person is close to the blast area, he might get injured and may lose mobility, which would restrict his behavior. Hence a detailed synthetic population has been modeled in a way that in addition to giving information about demographics, also includes information about the daily routine of each individual.

Below we describe briefly how the synthetic population is generated for the simulation. Much more detail, including detailed validation information, is presented elsewhere [2].

3.1 Base Population (Residents)

The population is generated in a series of steps.

Generating individuals and households—Demographic distributions and sample household information from the American Community Survey (ACS) are used to create a disaggregated population, which consists of a set of synthetic households and a set of synthetic individuals. This is done by using an algorithm known as iterative proportional fitting to generate a joint distribution, which is then sampled [11]. The generated synthetic population matches marginal demographic distributions from the ACS at the block group level, while preserving anonymity of individuals.

Locating households—Each synthetic household is assigned a housing location along a street using housing unit distributions from the ACS and street data from HERE (formerly Navteq).

Assigning activities—Each individual is assigned a set of activities to perform during a day, along with the time. The National Household Travel Survey (NHTS) and the National Center for Education Statistics (NCES) are used to create activity templates. Each synthetic household is matched to a survey household based on demographics, and individuals in the synthetic household are assigned the corresponding activities.

Locating activities—An appropriate location (essentially a building) is chosen for each activity of each individual using a gravity model and Dun & Bradstreet location data.

3.2 Transient Population

The method used to create the transient population follows the same methodology as used for creating the base population, but using different data sources. Destination DC[3] provides demographic information about leisure and business travelers in Washington DC. These demographic data are used to create a synthetic population of transients. Destination DC estimates that there are approximately 50,000 transients in Washington DC on any given

[3] http://washington.org

day. The transient population agents are divided into groups called parties, e.g., a family of tourists traveling together. Each party is placed in a hotel which serves as their home location for the purpose of visit. All individuals in a party are assumed to travel together and hence assigned the same activities. Each activity is represented by the type of activity (i.e., staying in a hotel, tourism, going to restaurants, work in case of business travelers), start time, duration and location. Various activity locations have been identified from Dun & Brad-street data based on SIC (Standard Industrial Classification) codes. Activity assignment is calibrated by matching visit counts at Smithsonian Institution locations, which are the largest draw for tourists.

3.3 Dorm Student Population

A synthetic population of college students living in dormitories is created separately for major colleges in the DSA. Data about the number of dorm students in each college and college boundary are obtained from CityTownInfo[4] and the District of Columbia public access online Data Catalog[5] respectively. For simplicity, students are assigned only two types of activities, staying in the dorm and school activities located at any of the locations within their college campus.

All the data sets used are summarized in Table 1. The total size of the synthetic population for the Washington DC metro area is over 4 million. The total number of agents in the simulation is 730,833, which is the subset of individuals within the DSA at the time of the event, and the total number of locations within the DSA is 146,337.

3.4 Validation of the synthetic population

A large, complex agent-based model such as this needs to be validated at every step. Each stage of the population construction methodology has been validated in prior publications, as we briefly describe below. Additional details can be found in a technical report [2].

IPF actually guarantees that for the variables which are included in the construction of the joint distribution, the marginals will be preserved [11]. Additional validation is carried out by comparing the distributions of variables that are not included in the IPF step with their distributions as given by the ACS. For example, the ACS provides the distribution of the number of workers in the family for each block group. This variable is not included in the IPF step but is included in the sample data, and is therefore carried along into the synthetic population when we copy the records from the sample data to create the synthetic population. We can therefore compare the distribution of the number of workers in the family in the synthetic population with the true distribution given by the ACS tables. This validation procedure consistently shows a close match between the synthetic population and the true distributions from the ACS.

Activity assignment is validated by comparing the average time spent in various activities broken down by age and gender between the survey data and the synthetic population. Our methods capture differences by age and gender accurately [29].

[4] http://www.citytowninfo.com/
[5] http://data.dc.gov

The location choice model has been validated extensively by Beckman et al. [9]. They extended the synthetic population to model cell phone traffic by integrating it with a model of the cellular infrastructure, and showed that they are able to match various measures of cellular traffic. This indirectly shows that the mobility model gives a good representation of actual population densities across the region over time. They also showed that the distribution of distances traveled is a power law, which is consistent with what has been reported in the literature [20]. The mobility patterns have also been validated using various measures of traffic such as trip counts between various zones [18].

4 Agent Design

Multiagent models allow each individual to be modeled as an autonomous agent capable of perceiving informational and environmental cues and interacting with other agents and the environment accordingly. As a result, agent-based methods have been used for evacuation simulations [27,32,39]. Simplistic models focus on physical interactions between individuals [27]. Somewhat more detailed simulations model agents with psychological models, though they haven't included infrastructural aspects [34,37]. Tsai et al. [39] and Pan et al. [32] model individual movement towards building exits and behavioral aspects like family influence and following the group leader in simulations of emergency evacuation of indoor spaces. Our goal here is not only to model evacuation-related movement and behavior but also to model other behavioral characteristics of humans in crisis (like helping others, sheltering in place, etc.) to understand the interactions between natural human behavioral instincts and external interventions.

Apart from demographics and location (derived from the synthetic population), agents are defined by a number of state variables like health (section 4.4), behavior (described next), mobility, if it is out of the affected area, time of the last call, if last call was successful, if received an emergency broadcast, etc. [33].

We develop five behavior models with progressively increasing complexity. They are derived from earlier studies of NPS-1 and studies from the literature of human behavior in disasters.

4.1 Null behavior model

Earlier studies of detonation of nuclear devices have mainly focused on evaluating the physical impact. They model the physical impact of the blast in terms of thermal, radiation, and fallout effects, and use static geographic distributions of the population during daytime or at night time (from Landscan data, e.g.) to calculate effects on human life. They assume that there is no response to the event from individuals; they just stay at the same location (outside, without any protection from radiation) where they were when the blast happened.

We model this scenario as "Null behavior" where there is no behavioral response to the event. This serves as the base case scenario. In our model, initial locations for agents are as derived from the synthetic population. Agents who are outside (on roads) are assumed to be exposed to radiation, similar to earlier studies. But for agents who are inside building at the time of detonation, we also take into account building damage and the reduction in radiation exposure due to the building based on the building construction material, following the work of Buddemeier et. al [12].

4.2 Early and delayed evacuation models

Recent work in this area has focused on modeling and evaluating sheltering versus evacuation strategies [15,12,40]. We particularly follow the model of Wein et. al [40], which models two types of behaviors: delayed evacuation (corresponding to sheltering) and early evacuation. In this model, each individual chooses between these two behaviors in the aftermath of the detonation. In delayed evacuation behavior, an individual shelters in place for an extended period of time before the responders arrange for evacuation. For people who choose to evacuate early, the evacuation time consists of diffusion time and preparation time. Preparation time is assumed to be 15 minutes for everyone. Diffusion time depends upon personal and interpersonal situational awareness and hence their distance from ground zero. If the distance is less than r_p, where r_p is the distance where people are directly aware of nuclear detonation, the diffusion time is zero. If the distance is greater than r_i, where r_i is the minimum distance at which electronic communication (phone, television, internet) work, the diffusion time is one hour. Between these two distances, people rely on others for information about the event, and the diffusion time is assumed to be three hours.

We set r_p to 4 km, which is the distance at which windows break. This represents low situational awareness. r_i assumed to be 17 km, following the work of Wein et al. [40].

In our model, we assume that a building is appropriate for shelter if it is less than 10% damaged. An individual who decided to shelter but is outside, or in a damaged building, travels to a nearby good quality location and shelters there. We also model early and delayed evacuation to be self-evacuation without help from responders. When evacuating, an agent travels to the nearest evacuation location. Evacuation locations are points on major highways just outside the DSA.

4.3 Behaviors derived from literature

There have been multiple surveys and analyses, both prospective and retrospective, of human behavior in disasters. They provide insight into different kinds of behaviors.

- *Sheltering, seeking family members, communication*: In many surveys [21, 24] about the aftermath of a dirty bomb scenario, most people responded that they would try to leave the area if not asked to shelter in place. The main reason for individuals to leave is concern for people dependent upon them and other family members [21,24,25]. However, people would stay in-place if they are able to communicate with their family members [24].
- *Evacuating only after finding family members*: If an emergency happens during the day time, members of a family are likely to be scattered across the region (for daily activities like work, school, etc.). In such cases family members try to gather children [28] and each other and evacuate as a single unit [16].

- *Delay in evacuation*: It is also observed that in an emergency without warning (such as terrorist attack), there is some delay between the time at which the initial cues occur that an emergency is taking place and the time people start evacuating based on their perception of risk, which is based on environmental cues (e.g., smoke, debris), behavior of others, and past experience [36].
- *Aiding and assisting, seeking healthcare*: Contrary to the assumption that trained emergency personnel carry out field search and rescue, studies show that most initial search and rescue is carried out by survivors [6,35]. Also survivors and most casualties are more likely to go to the nearest hospital.

We use these findings to build our behavior models. Apart from the state variables described earlier, each agent keeps track of **knowledge about family members' health states** which could be unknown, known to be healthy, or known to be injured. This knowledge is updated whenever it makes a successful call to a family member or meets them in person.

We also model **follow the leader behavior**, i.e., once family members encounter each other, they move together from there on. One of them becomes the leader and others follow him. This kind of behavior is well-documented in emergency situations [16,28]. Similarly when a person is rescued by someone he travels with him until he reaches hospital or meets his family members.

Here, agent behavior is modeled based on the representation of decentralized semi-Markov decision processes (Dec-SMDP) with communication [19], using the framework of options [38]. Here, high-level behaviors are modeled as options, which are policies with initiation and termination conditions. We model six behavior options: evacuation, shelter-seeking, healthcare-seeking, worry, household reconstitution, and aid & assist. High-level behavior options correspond to low-level action plans which model their dependency with infrastructural systems. These actions are: call, text or move. Whom to call or text and where to move depend upon the current behavior option, e.g., in the household reconstitution option, a person tries to call or to move towards his family members, while in the healthcare-seeking option, a person tries to call 911 or move towards a hospital.

At each iteration, for each agent, behavior is updated by first checking the termination condition for the current behavior option. If it is terminated, a new behavior option is chosen based on the circumstances of the agent. Various factors affecting human behavior are organized in a decision tree where leaf nodes contain probability distributions for behavior option selection (see Section 5). Then, a new action (call, text or move) is chosen for the current behavior option. Agent movements are taken care of by the transportation module [4,3] which includes road, bus, and metro networks. Agent calls and texts are taken care of by the communication module [13] which also takes into account phone availability, battery life, reception, and bandwidth.

It is hard to obtain exact probabilities for each behavior option and action in all circumstances from the literature. The values used for the simulation are shown in the figures, however they could be changed if necessary.

High level behavior options are policies with initiation and termination conditions. Initiation conditions are paths followed in the decision tree. Policies and termination conditions are as described below:

4.3.1 Shelter-seeking (Shelter)—This represents individual behavior of staying inside a building in order to shelter from radiation. A building is designated a shelter location if it has less than 10% damage, though this may not correspond to an equal reduction in exposure as compared to being outdoors, since the reduction in exposure depends on the construction materials of the building and other factors. Detailed data about building conditions were available to us and were incorporated into the model.

Action Selection: If an agent is in a location that provides shelter then it stays there otherwise it tries to move to the nearest shelter location.

Termination Condition: An agent terminates this behavior if its health state falls below 5, or with probability $(1 - r)$, where r is percentage radiation attenuated by being inside a building at this location. Some agents are not patient enough to remain in shelter for a long period of time and hence with probability 0.1, they randomly terminate this option.

4.3.2 Evacuation (Evac)—This models individual behavior to evacuate the affected region and move to a safe area. Evacuation destinations are chosen to be points on major highways just outside the DSA.

Action Selection: An agent attempts to move to the nearest evacuation location. In addition, with probability 0.5, an agent also tries to call all his family members who are not together with him every hour.

Termination Condition: If a person is in poor health ($healthstate < 5$) or is unable to move then this option is terminated.

4.3.3 Healthcare-seeking (Health)—This models behavior of a sick or injured agent to seek a health care facility.

Action Selection: If an agent is unable to move, it calls 911. If the last call to 911 was successful, then the agent is “teleported” to the nearest health care location with probability 0.2 to mimic being rescued by an ambulance (this probability is low as initially most casualties come to hospital by private vehicle [6]). Otherwise the agent moves toward the nearest healthcare location.

Termination Condition: If an agent is unable to move and all calls attempted fail, then the option is terminated. Otherwise, if the agent is rescued by somebody in “aid & assist” option, or the agent reaches a hospital then this option is terminated.

4.3.4 Worry—It may be expected that a disaster of this magnitude would cause worry in some people. Here, worry covers anxiety, information seeking, and "worried well patient" behavior.

Action Selection: The action performed by an individual when worried is as shown in fig. 5 where "callFlag" means that with probability 0.7, the agent has chosen to call 911, "goOutside" means that with probability 0.5, the agent has chosen to run outside the building (this probability is 0 if the agent is too injured or sick to move), "goHospital" means that with probability 0.3, the agent attempts to move towards a hospital (regardless of its health state).

Termination Condition: People are assumed to be more likely to worry initially than later, hence if the time elapsed since the event is more than 3 hours then with probability 0.5 the agent quits the worry option. To avoid a sharp transition where everyone stops worrying at once, we use a sigmoid function to smooth the probability of quitting the worry option around the 3 hour mark. Alternatively, if an agent has received an emergency broadcast or has made a successful call to 911 then it is less likely to worry, and hence quits the worry option with probability 0.75 and 0.5, respectively.

4.3.5 Household Reconstitution Option (HRO)—Household reconstitution (seeking family members or information about them) is the most natural human behavior in emergency situations.

Action Selection: If person does not have any family member, then he moves to the nearest evacuation location, otherwise the action taken is as shown in Figure 6, where "AllKnown" means the health status of all household members is known.

Termination Condition: The HRO option is terminated if all family members are at the same location (i.e., they have successfully reconstituted their household). It is terminated with probability 0.5 if somebody in the group is in poor health ($healthstate < 5$, indicating moderate injury or worse), or if it is known that all family members are safe or if somebody in the group has received an emergency broadcast.

4.3.6 Aid & Assist (A&A)—This models the (survivor) behavior of assisting children (age < 5 years), sick people, or individuals who are unable to move due to injury.

Action Selection: The algorithm is shown in Figure 7.

Termination Condition: An agent quits this behavior if it is sick, unable to move, or somebody in its family is not safe. An agent also quits this option if it is unable to find another agent to rescue at the current location.

4.4 Health Modeling

The health of a person will drive their behaviors, affect their mobility, and influence the time needed for healthcare. For these purposes a simple model that represents health on a continuum for injury triage (based on the SALT triage [1]) is used as the main health state.

This continuum consists of states from 0 (death) to 7 (full health), with states 4 and lower corresponding to moderate injury or worse. Secondary effects of health (mobility, health care requirements, etc.) are calculated based on this state. Additionally, processing individuals for treatment and calculating their response to treatment is also based on these states.

Initial injuries and their severity are calculated based on the physical properties of the blast itself, which has been extensively calculated. If the agent is outdoors, injuries can occur from the physical effects of the blast, which have been modeled to account for the effects of shielding from buildings. Similarly, individuals inside buildings are affected by physical effects of the blast, but can also be injured due to building collapse. Radiation from the blast is also attenuated by buildings and is absorbed by individuals, though the effects of this prompt radiation on the agent's health can be delayed over time.

Following the immediate effects of the blast, an agent's health can deteriorate as a function of time, cumulative radiation exposure, or from injuries suffered while moving over the damaged landscape. Health can be improved for agents who receive healthcare, or as a function of time (mainly for minor injuries). The delayed effects for the prompt radiation exposure from the blast are accounted for as they begin to manifest (for instance absorbing 2.5 Grays of radiation may induce a deterioration of health within 1–4 hours that may impede mobility). Similarly, physical injuries that go untreated for prolonged periods of time can cause delayed deteriorations in health. The likelihood of suffering a health changing injury are based on the physical attributes of the locations a person moves over, those with greater amounts of debris from collapsed buildings etc. are more likely to produce injuries.

The mobility of the individual depends on the severity of the injury, and the likelihood that the injury would prevent an agent from being able to walk (e.g., a broken leg impedes mobility, whereas a broken arm does not). If an agent is severely injured (health state 3) they are very unlikely to be mobile (90% are immobile).

For agents seeking healthcare, they initially seek it at DC area hospitals. As mobile healthcare units brought in by the federal government arrive agents that can see these locations and need health care will seek it there instead of the hospitals. The number of agents that can be treated and the degree of injuries that can be treated depend on the number of health care workers at each facility and the type of facility. Extremely mobile emergency response vehicles are the first to arrive within hours but can deliver very minimal care and larger mobile hospitals take days to arrive but can deliver a wider spectrum of care. Demand for healthcare quickly outpaces the rate, which depends the severity of the injury and number of health workers available, at which point it can be provided and a queue develops. Agents begin to leave the queue if their injuries are not severe (health state > 3) and the line is longer than 10000 agents.

5 Experiments

We perform a series of experiments starting from the "null behavior" scenario where people stay where they were at the time of the blast. This scenario serves as a base case.

Next, we follow the work of Wein et al. [40] which models two scenarios as described in section 4: delayed evacuation (corresponding to sheltering) and early evacuation. In the delayed evacuation scenario, 90% of the people choose to shelter for the initial 12 or 24 hours and then evacuate. For early evacuation scenario, 90% of the people decide to evacuate early and the rest of the people shelter for the initial 12 or 24 hours before evacuating. Results are similar with evacuation time set to 12 and 24 and hence we only present results with evacuation time 24 hours.

The fourth behavioral model adds in two more behaviors: healthcareseeking and worry. We refer to this as the four behavior model. To choose between options, we use a decision tree, illustrated in Figure 8.

Finally, we include all the behaviors described in Section 4 to create the six behavior model. The decision tree for selecting options in this model is illustrated in Figure 9.

The specific decision of which behaviors to include in the four-behavior model are based on the fact that healthcare-seeking and worry can be treated as largely individual behaviors (as sheltering and evacuation are also being treated), whereas household reconstitution and aid & assist are group behaviors. As we will see in the experiments to follow, including group behavior, especially household reconstitution, has a major impact on the population movement dynamics.

In these decision trees, probabilities at the leaf nodes are set as a best guess. The literature on human behavior in disasters is largely qualitative, and does not offer much guidance on how to set these probabilities. As it takes over 24 hours to run one simulation, it would take a long time to carry out full set of experiments to evaluate the sensitivity of results to these probabilities. Here, we evaluate sensitivity due to two factors. The first factor is probability of sheltering on receiving emergency broadcast (denoted by p in Figures 8 and 9), as sheltering is the recommended strategy in case of a nuclear explosion to minimize radiation exposure. We assume that authorities would send out notifications on cell phones, providing information about the event and asking people to shelter. However, surveys suggest that people may not comply with it due to concern for family members [21,24,25]. Hence, we try two values of this factor: 0.1 for the worst-case scenario and 0.9 for the best-case scenario. The second factor is the probability of worry (or information-seeking) behavior in first few hours (about 3 hours) when emergency broadcasts are not received (denoted by q in Figures 8 and 9). We try two values: 0.3 for low worry and 0.6 for high worry levels. Two factors, each with two values, result in a four cell experiment as shown in Table 5.

We run 5 simulations (called runs) for each scenario. Each simulation consists of 100 iterations (time steps) where first 6 iterations represent 10 minute intervals and the rest are for 30 minute intervals, which results in a total simulated time of 2 days (48 hours). Since radiation levels vary sharply in the first hour, smaller time intervals are simulated for the first hour.

To evaluate sensitivity of results due to stochastic factors in the model, outcomes from each individual run are presented in the Supplementary Information. Results show that for all models, outcomes in terms of number of people dead, number of people with low health, number of people moving within 1 mile of ground zero, average distance (meters) from ground zero (except for six behavior (cell 3) model), number of people with very high exposure (centiGrays), and number of people out of area, are not very sensitive to the stochastic factors. However, plots for number of people who received treatment show two different trajectories for the four-behavior (cells 1, 2, and 3) and six-behavior (cells 2 and 3) models and hence, are somewhat sensitive to stochastic factors. For the six-behavior (cell 3) model, the plot for average distance (meters) from ground zero also shows two trajectories and hence, it is also a little sensitive to the stochastic factors in the model. From here on, we present results in terms of averages across 5 runs.

Figure 10 plots the number of people dead for each scenario. As expected, the highest number of people die in “null behavior” scenario as people do not move from their initial location. In all scenarios, we estimate that ~18,000 people die immediately after the detonation, and ~90,000 are dead (total) after the first ten minutes. This is slightly higher than the estimates by Wein et al. [40], who obtain an estimate of ~80,000 dead due to prompt effects.

We see that the number dead in all our scenarios is approximately the same for the first two hours, after which the null behavior scenario starts to increase more rapidly than the others. At the end of 48 hours, 279,020 people are dead in the null scenario. We treat this scenario as the base case and compare all other scenarios with respect to it.

Figures 11(a) and 11(b) plot the differences in number of people dead and with low health (moderately or more injured) as compared to null behavior. In the simulation, low health is defined as healthstate < 5. Overall, the four-behavior model with low worry scenarios (cells 1 and 3) have the best final outcome with ~28,400 fewer people dead and ~69,850 fewer people in low health as compared to the null behavior model. While the six-behavior model with high worry scenarios (cells 2 and 4) have the worst outcome (after null behavior scenario) with only ~20,200 and ~50,650 fewer people dead and in low health, respectively, as compared to the null behavior scenario.

Initially, delayed evacuation has the highest positive impact on health as compared to other scenarios (Fig. 11(b)). This is because in first few hours, when radiation exposure is high, most people are sheltering in the delayed evacuation scenario and hence are exposed to less radiation. While in other scenarios, people are involved in other behavior options which make them go outside and be exposed to radiation. However, in long run, four-behavior with low worry scenarios (cells 1 and 3) have better outcomes. This is because, in a few hours (about 8 hours, iteration 20), some people in the four-behavior and six-behavior scenarios who were seeking healthcare are able to reach health-care locations and get treated. This makes the outcomes in the four-behavior with low worry scenarios as good as the delayed evacuation scenario. Figure 12(a) shows the differences in the numbers of people receiving healthcare in each scenario as compared to the null scenario. Surprisingly, more people (about 7,000 to 20,000 more people as compared to four-behavior with low worry scenario) get treatment in the four-behavior with high worry scenarios and all six-behavior scenarios. However, many people (about 5,000 to 15,000 more people as compared to the four-behavior with low worry scenario) also come closer to ground zero looking for their family members which outweighs the benefits of receiving healthcare. Figure 12(b) shows the differences in the numbers of people who started outside 1 mile radius from ground zero and are within 1 mile radius over the course of the simulation.

We see in Figure 12(b) that even in the delayed and early evacuation scenarios, ~5,000 people who start outside the 1 mile circle come within the 1 mile circle. This is because people who are just outside this boundary may move within 1 mile of ground zero as they seek out a building that provides shelter. However, the biggest difference we see is for the six-behavior scenarios. About 23,000 and 25,000 people move into the area within 1 mile of ground zero for low and high worry scenarios, respectively, as they seek out their family members and to a smaller extent, to aid & assist others. This means they get exposed to high levels of radiation and risk other injuries as they travel over a damaged landscape. This is the biggest contributor to the lower health outcomes in six-behavior scenarios.

Overall, the six-behavior scenarios have the worst impact in terms of number of people dead and injured as, on average, people have not moved much further from where they started. Figure 13(a) shows the differences in average distance from ground zero as compared to the null behavior scenario. In fact, the difference is positive at first for the six-behavior scenarios because of the large number of people moving towards ground zero. This means that there are a greater number of people subjected to very high levels of cumulative radiation exposure (Figure 13(b)). In the early evacuation scenario, people start evacuating earlier and get out of the region sooner (Figure 14) which results in less exposure and hence does better than the six-behavior scenarios.

Both the early evacuation and delayed evacuation scenario show a spike at iteration 53, which corresponds to the time (24 hours after the detonation) when the population still sheltering starts evacuating. Their evacuation routes might take them slightly closer to ground zero than they were, which is why we see the jump in those curves in Fig. 13(a). As Fig. 13(b) shows, however, this short-lived spike in the average distance does not make a difference in the number of people with very high exposure.

Once people who were sheltering start evacuating (for the delayed evacuation scenario), they are exposed to radiation. So benefits of treatment make results in the four-behavior with low worry scenario better than delayed evacuation scenario in long run, though these are not enough to overcome the negative consequences of large numbers of people moving towards ground zero in the four-behavior with high worry and all six-behavior scenarios.

Finally, we see in Figure 14 the differences in the numbers of people who have evacuated the DSA. We see that the largest number of people who evacuate successfully are in the early evacuation scenario where over 500,000 people end up outside the study area in 48 hours. In four and six behavior scenarios, only 402,000 to 424,000 people end up outside the study area in 48 hours. However, as we have seen, health outcomes are the best in the four-behavior scenario. This shows us that we should not conflate evacuation with better health outcomes.

For both four-behavior and six-behavior models, health outcomes (Figures 11(a) and 11(b)) are worse in high worry scenarios (cells 2 and 4) as compared to corresponding low worry scenarios (cells 1 and 3, respectively). When people are worried, they run outside or call 911, looking for information, or go to the nearest healthcare location. So in high worry scenarios, more people (about 4,000 to 7,000 more) get treatment (Figure 12(a)) but also more people (about 1,000 to 5,000) move within 1 mile ground zero (looking for the nearest hospital; Figure 12(b)) and hence are exposed to very high levels of radiation (Figure 13(b)). This makes outcomes in high worry scenarios worse than corresponding low worry scenarios. As more people are worried in high worry scenarios, they also evacuate slower and about 14,000 to 20,000 fewer people are out of the area in 48 hours, as compared to the corresponding low worry scenarios.

The blast destroys cell phone communication towers in the nearby area (Severe Damage Zone). In our earlier work [31], we have shown (for six-behavior with low worry model) that without restoring communication (at least partially), increasing the probability of sheltering does not help. Here also, health outcomes (i.e., number of people dead and injured) are similar for cells 1 and 3 as well as for cells 2 and 4 for both, four-behavior and six-behavior models.

This is because, in these scenarios, communication is not restored and so people who are close to ground zero and are exposed to high levels of radiation do not receive emergency broadcasts and do not shelter.

5.1 Sensitivity Analysis

The input parameters and models in simulation experiments in this paper are designed so that those parameters and models that most influence the simulations can be determined. Here, the parameters and models form a 2^3 factorial experiment: all combinations of two probabilities each for sheltering and worry, and two models. Each combination is simulated five times, as mentioned earlier.

The factor or factors (shelter, worry, models) that most influence the total number of deaths by iteration 100 are shown in Figure 15. using an analysis plotting procedure [10].

In Figure 15, the numbers of deaths, averaged over the five replicates, are shown by the small circles. The standard deviations around these means are denoted as dashed horizontal lines. The solid lines and the vertical dashed line have no scientific meaning, but are included to guide the eye. The order of the variables on the x-axis is critical. It is based on an analysis of variance where the most significant variable is at the bottom of the plot, followed by the next most significant etc. In these experiments the Model effect is much greater that the effects of worry or shelter. The worry probabilities are the second most influential variable on the number of deaths. The effect of shelter is not statistically significant.

It is clear from Figure 15 that the number of deaths is greatly increased by adopting the six-behavior model rather than the four-behavior model. The effect due to the differences in the models is almost an order of magnitude larger than the effect of the next most “important” variable worry, while in these simulations there is no effect (within variability) due to shelter.

The six-behavior model adds two behavioral options (household reconstitution and aid & assist) to the four-behavior model. The difference in number of deaths between these two models is mainly due to the inclusion of the household reconstitution behavior. In this behavior, people are looking for family members which brings many of them come close to ground zero and exposed to high levels of radiation.

In the worry behavior, people run outside looking for information or go to nearest hospital, exposing themselves to radiation, which causes it to have the next largest effect on total number of deaths.

6 Discussion

The main observations that can be made from comparing the different behavior models are as follows.

First, the null model substantially over-estimates the number of casualties and mortalities compared to all the other models. Thus, the general approach of including human behavior in the study of this scenario is important.

Second, it may be considered that early evacuation and delayed evacuation represent two extremes of outcomes in the sense that they will lead to two extremes of radiation exposure and therefore two extremes of health outcomes. In fact, we see that the four-behavior scenario results in a better outcome than both of the previous two scenarios because we are taking into account healthcare-seeking behavior.

On the other hand, the six-behavior scenario leads to worse outcomes than all previous scenarios because a large number of people enter the region close to ground zero. This more than offsets the gains due to healthcare-seeking behavior.

This also means that, as we keep adding behaviors to the model, the outcomes don't change monotonically. Some behaviors lead to improvements in outcomes, and some lead to a worsening of outcomes. This suggests that we must be careful to try to include all the relevant behaviors because it may be difficult to predict which behaviors are going to have the biggest impact on outcomes and what the aggregate outcome of combining multiple behaviors will be.

The model we have developed is a platform that allows investigation of many other questions as well. In other work, we have looked at the effects of sending emergency broadcasts via cell phones to inform people of what has happened and to advise them to shelter in place [13,31]. This work showed that unless communication is restored (at least partially) in the region within 1 mile of ground zero, emergency broadcasts would not have a significant benefit. However, if communication can be restored rapidly (using Cells-on-Wheels, e.g.), then sending emergency broadcasts can have a significant benefit. Restoring communications also helps because people can get in touch with their family members. Once they find that their family members are safe, they are more likely to shelter themselves. In this sense, restoring communications helps to channel people's natural instincts for seeking out family members in a positive direction.

7 Conclusion

In this work, we have described a detailed agent-based simulation of the National Planning Scenario 1. In addition to a realistic agent population, the simulation also models multiple infrastructures and their interaction with the population.

We have developed five behavior models of increasingly complexity. These models are based on prior work in this domain as well as empirically established facts about human behavior in disasters.

We have presented a series of experiments to compare the five behavior models and found that increasing the number of behaviors has nonlinear and non-monotonic impacts on the outcomes of the simulation.

This work, and more broadly, this line of research, has important policy implications as well. One important point to note is that many people will not know what has happened. This problem will be exacerbated by the fact that communications will be affected. This means that it is unreasonable to expect people to shelter, especially for as long as 12 or 24 hours. As people leave their locations to seek information, to seek healthcare, and to seek family members, they will be exposed to multiple hazards, including direct radiation, fallout, damaged buildings and roads, and more.

In such a situation, it is useful to have tools that allow representing the detail and complexity of human behaviors and their interactions with each other and with the infrastructure. This type of a tool constitutes a platform which can be used for evaluating policies through multiple what-if scenarios. Representing a diverse range of behaviors is essential to understand the range of possible outcomes.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

Supported in part by DTRA CNIMS Contract HDTRA1-11-D-0016-0001, DTRA Grant HDTRA1-11-1-0016, NSF NetSE Grant CNS-1011769, NIH Grant 1R01GM109718, NSF SDCI Grant OCI-1032677, and NIH MIDAS Grant 5U01GM070694-11

We thank our external collaborators and members of the Network Dynamics and Simulation Science Laboratory (NDSSL) for their suggestions and comments. This work has been supported in part by DTRA CNIMS Contract HDTRA1-11-D-00160001, DTRA Grant HDTRA1-11-1-0016, NIH MIDAS Grant 5U01GM070694-11, NIH Grant 1R01GM109718, NSF NetSE Grant CNS-1011769, and NSF SDCI Grant OCI-1032677.

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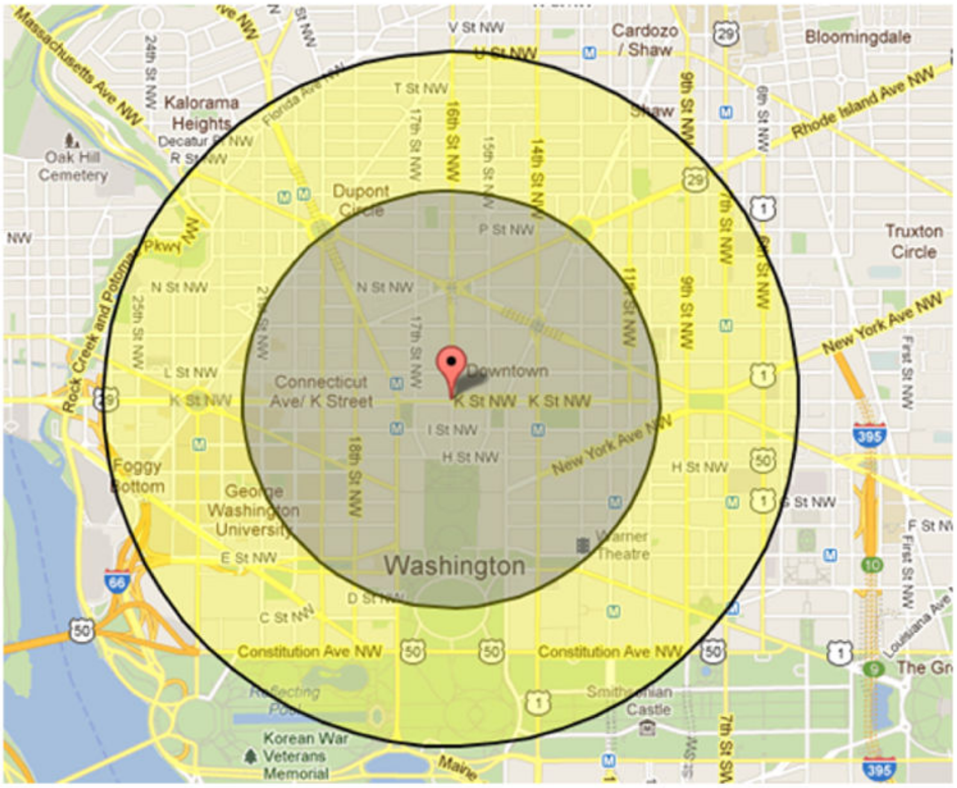


Fig. 1.

Damage zones in the study area. The inner circle corresponds to the expected Severe Damage Zone (SDZ), and the annular region around it is the expected Moderate Damage Zone (MDZ).

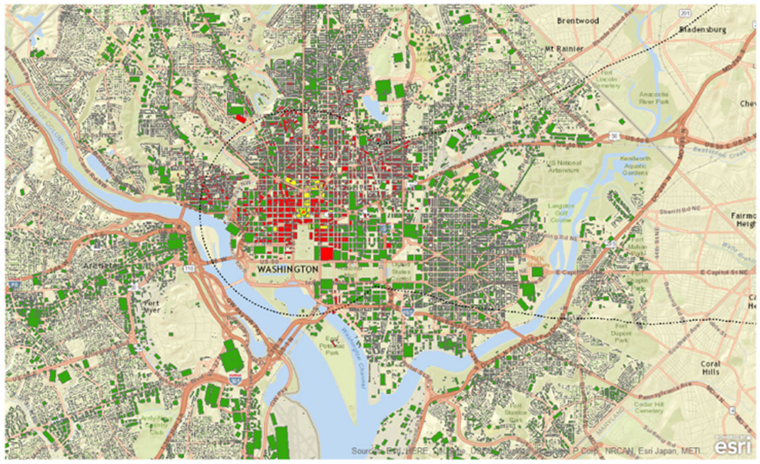


Fig. 2.
Damage to buildings. Red, yellow, and green correspond to severe, partial, and no damage, respectively.

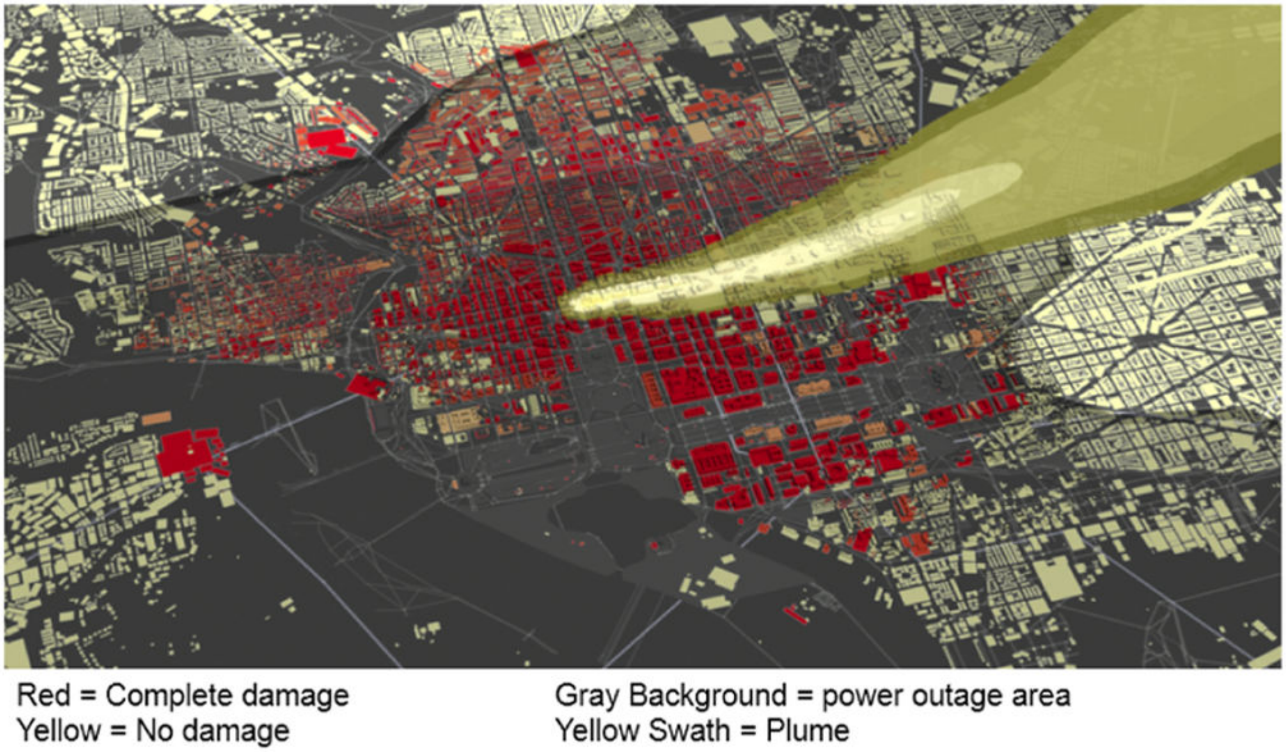


Fig. 3.

Building damage with the fallout contours.

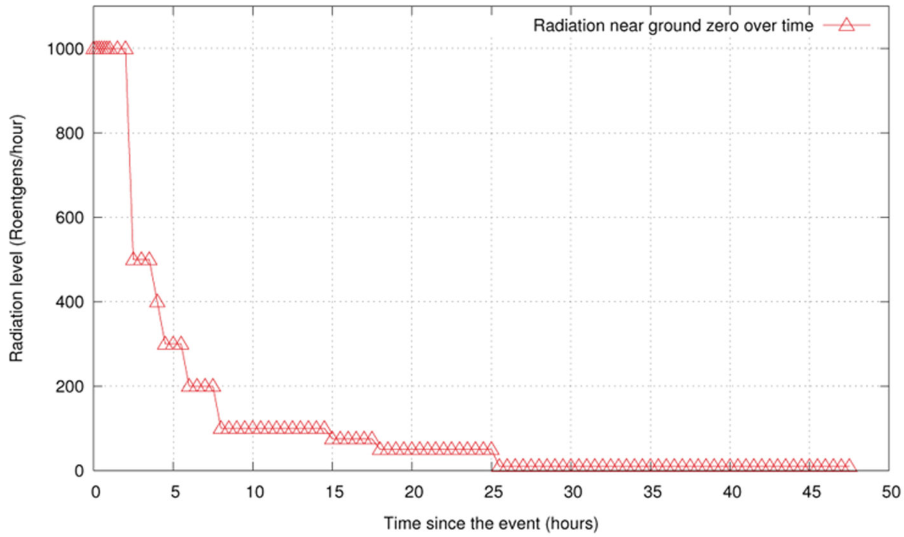


Fig. 4.

Radiation decay near ground zero over time.

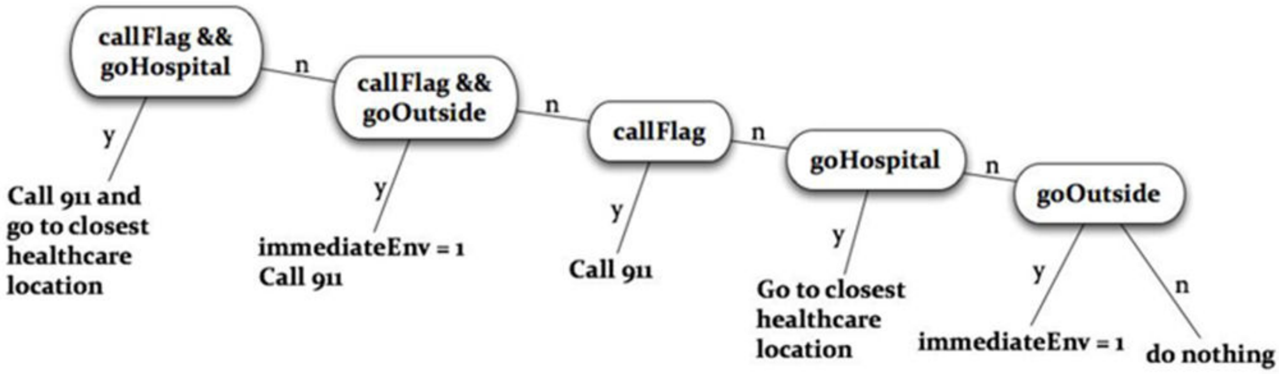


Fig. 5.
Decision tree for worry action selection.

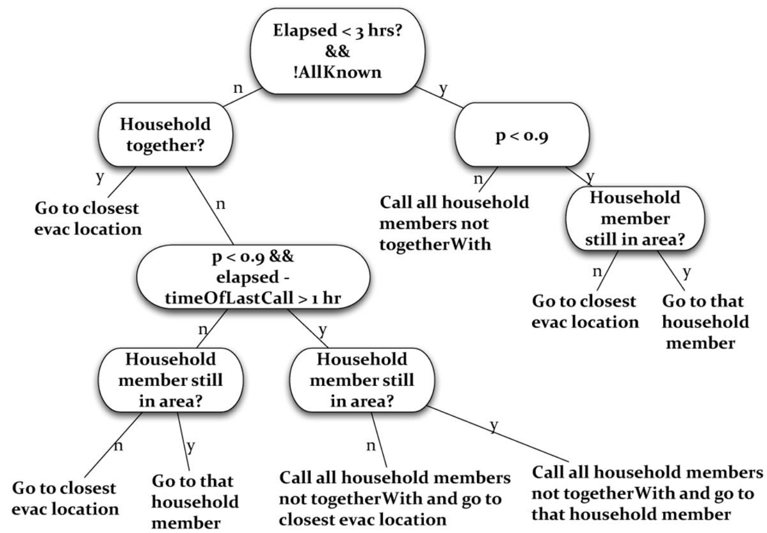


Fig. 6.

Algorithm for household reconstitution action selection.

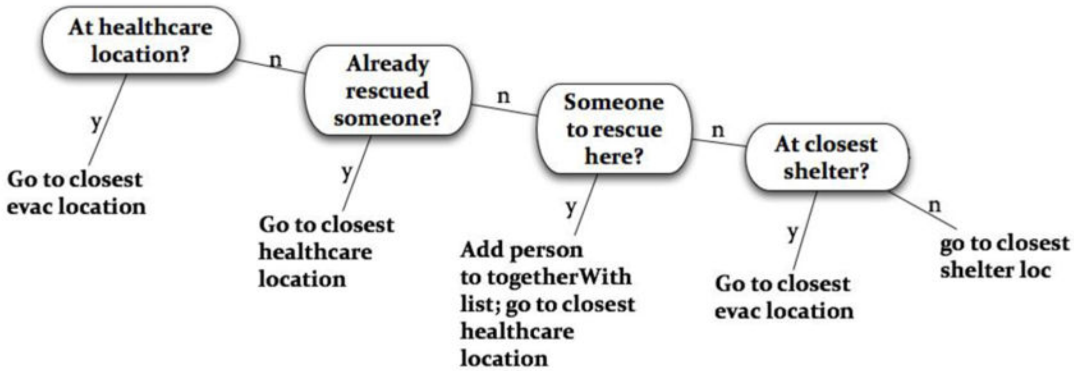


Fig. 7.
Decision tree for aid & assist action selection.

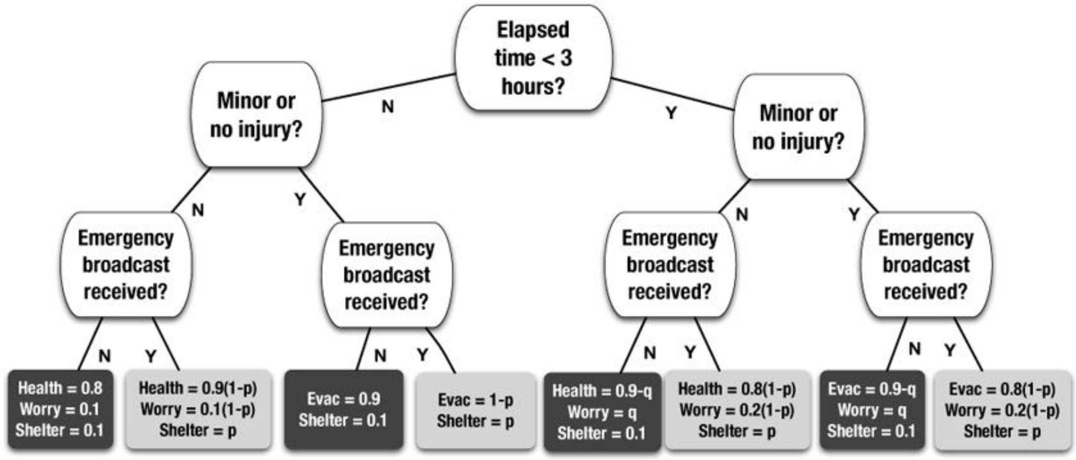


Fig. 8.

The four behavior model, which includes the shelter-seeking, evacuation, healthcareseeking, and worry behaviors.

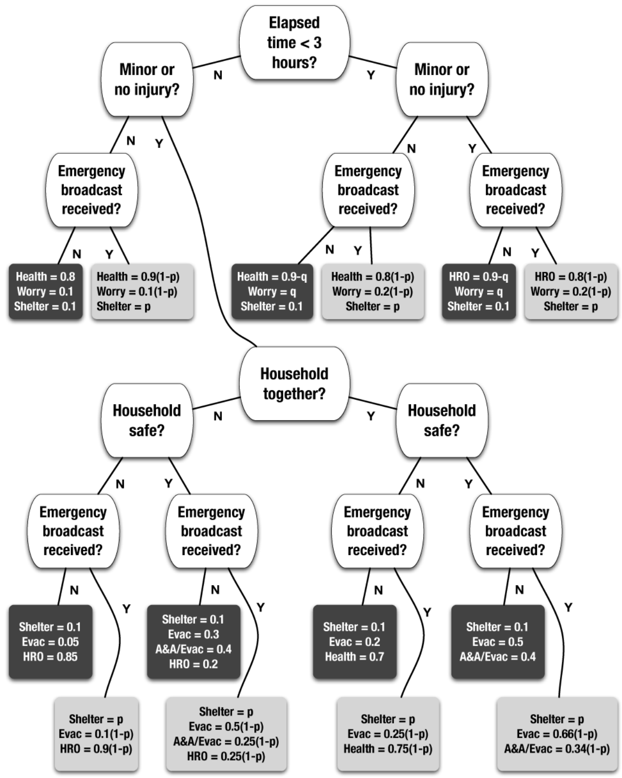


Fig. 9.

The six behavior model, which includes the shelter-seeking, evacuation, healthcareseeking, worry, household reconstitution (HRO), and aid & assist behaviors.

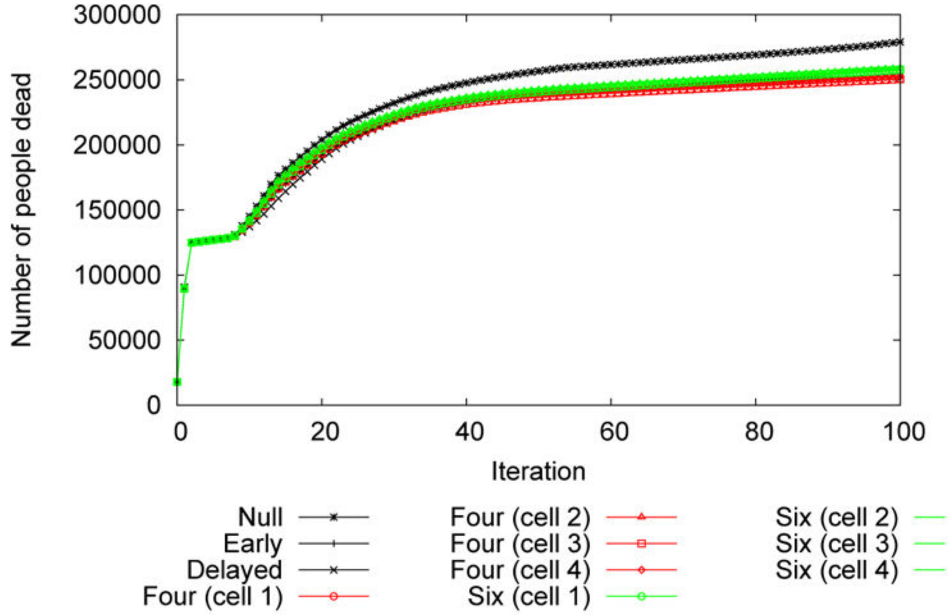
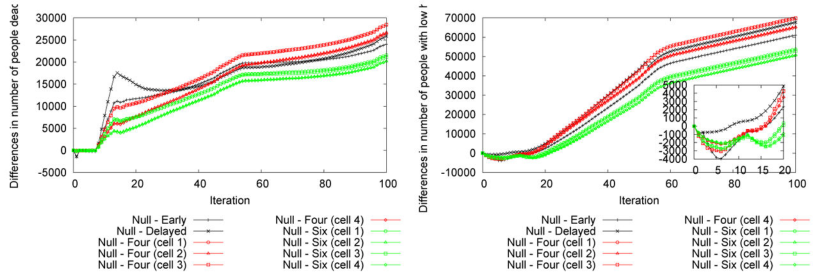


Fig. 10.

Number of people dead in all scenarios. Here, scenarios are labeled as follows: Null - Null behavior, Early - Early evacuation, Delayed - Delayed evacuation, Four - Four behavior, Six - Six behavior. Cells are defined as in Table 5.

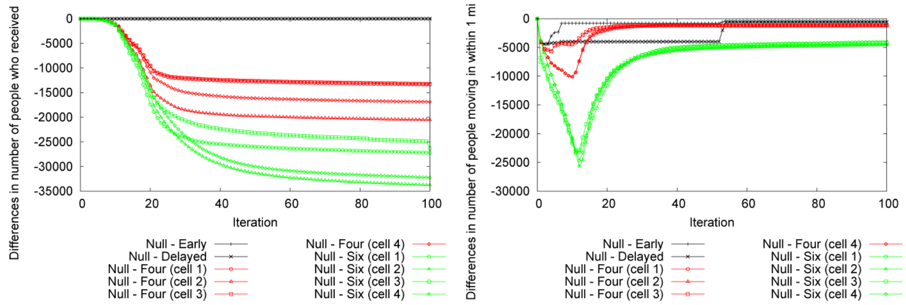


(a) Differences in number of people dead.

(b) Differences in number of people with low health. The inset zooms in on the first 20 iterations.

Fig. 11.

Differences in mortalities and casualties with respect to the null scenario.

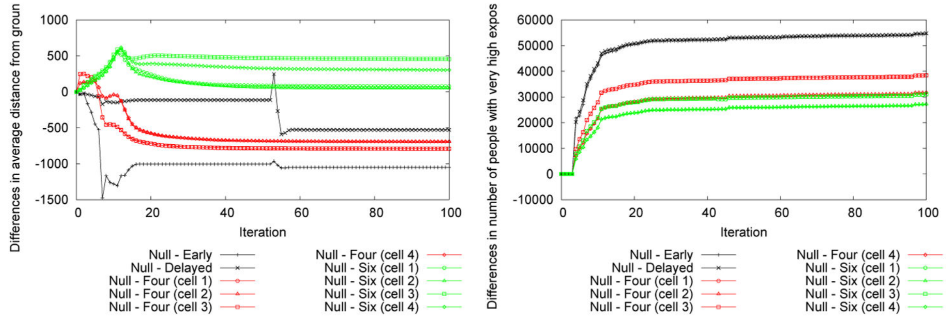


(a) Differences in number of people who received treatment

(b) Differences in number of people moving within 1 mile of ground zero

Fig. 12.

Differences in treatment and population movement with respect to the null scenario.



(a) Differences in average distance

(b) Differences in number of people with very high exposure (centiGrays)

Fig. 13.

Differences in distance and radiation exposure with respect to the null scenario.

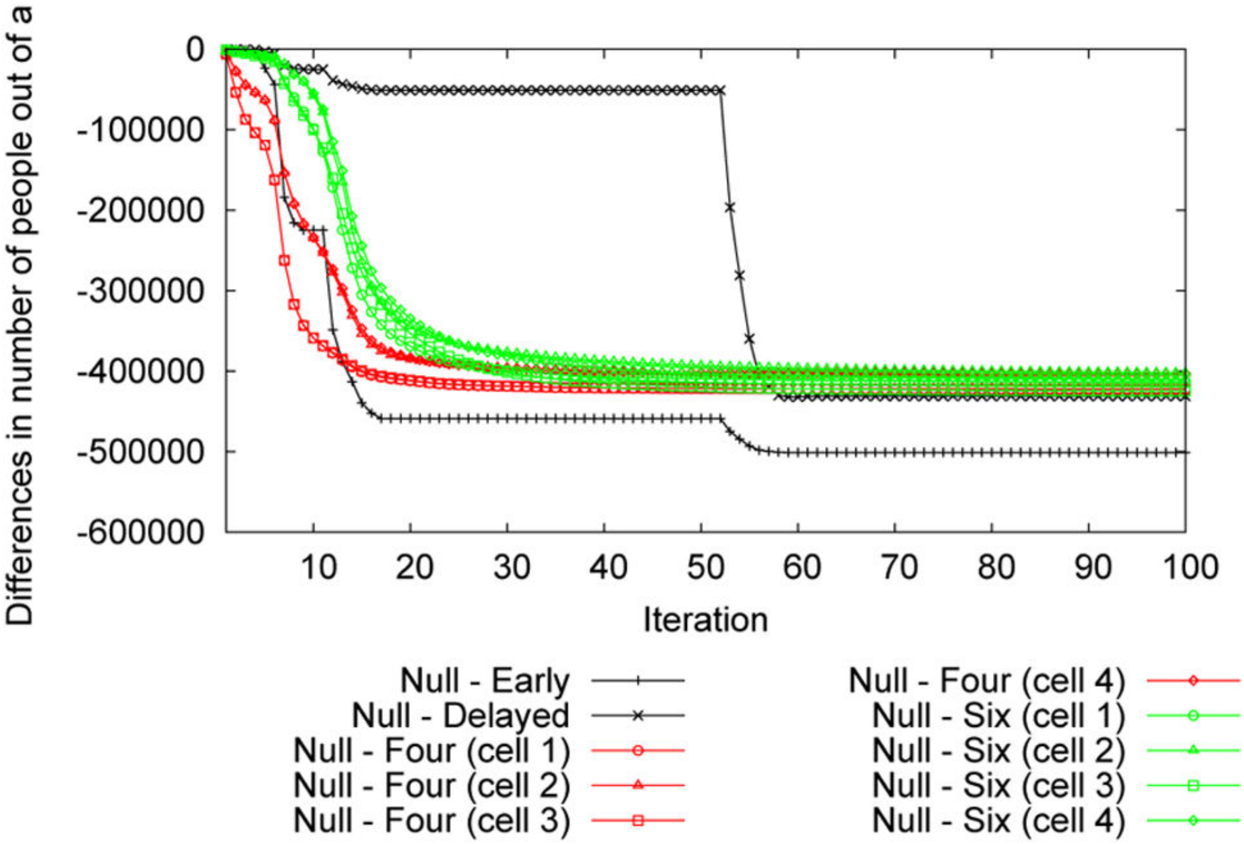


Fig. 14.
Differences in number of people out of area with respect to the null scenario.

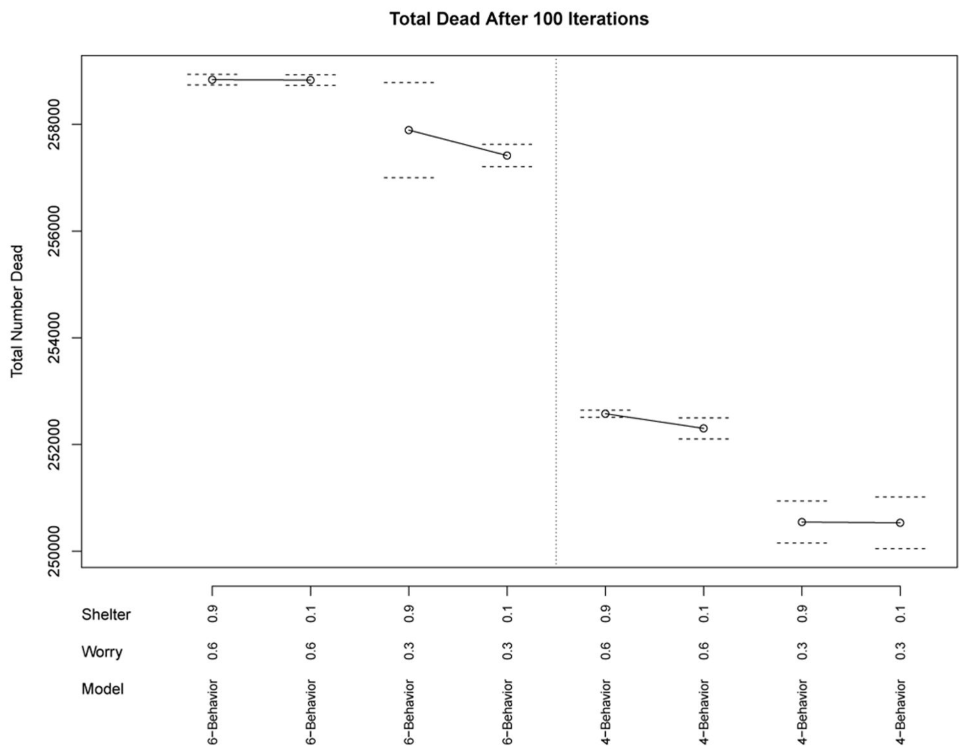


Fig. 15.

The total number of people dead at iteration 100 as a function of the two models, the two worry probabilities, and the two probabilities of shelter. Models have the most effect on death, followed by Worry. The effect of Shelter is not statistically significant.

Table 1

Datasets used for population generation.

Used for	Data sources
Base US population	American Community Survey National Center for Education Statistics National Household Travel Survey HERE (formerly Navteq) Dun & Bradstreet
Transient population (additional)	Destination DC Smithsonian visit counts
Dorm students (additional)	CityTownInfo DC public access online data catalog

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Table 2

Experiment design.

Cell	$P(Shelter \mid EBR)$	$P(Worry \mid t<3 \text{ hours, no } EBR)$
1	0.1	0.3
2	0.1	0.6
3	0.9	0.3
4	0.9	0.6