GIS and agent-based models for humanitarian assistance

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Abstract

Natural disasters such as earthquakes and tsunamis occur all over the world, altering the physical landscape and often severely disrupting people’s daily lives. Recently researchers’ attention has focused on using crowds of volunteers to help map the damaged infrastructure and devastation caused by natural disasters, such as those in Haiti and Pakistan. This data is extremely useful, as it is allows us to assess damage and thus aid the distribution of relief, but it tells us little about how the people in such areas will react to the devastation. This paper demonstrates a prototype spatially explicit agent-based model, created using crowdsourced geographic information and other sources of publicly available data, which can be used to study the aftermath of a catastrophic event. The specific case modelled here is the Haiti earthquake of January 2010. Crowdsourced data is used to build the initial populations of people affected by the event, to construct their environment, and to set their needs based on the damage to buildings. We explore how people react to the distribution of aid, as well as how rumours relating to aid availability propagate through the population. Such a model could potentially provide a link between socio-cultural information about the people affected and the relevant humanitarian relief organizations.

1. Introduction

Natural disasters such as earthquakes and tsunamis occur around the world, altering the physical landscape and causing severe disruption to people’s lives. All too often, these events occur in areas that lack the information resources and infrastructure to adequately respond to such challenges. The need for information is particularly pressing; to take aid distribution as an example, it is essential to identify where tents, food, water, and medical care are needed, and in what quantities (Benight et al., 1999). Accurate and current spatial data is a tremendous aid in humanitarian efforts, but more often than not in less developed counties this type of spatial data is lacking. Even in cases where spatial data is available, its temporal resolution often lags behind the situation on the ground. While incomplete, outdated, or simply absent data can seriously hamper relief efforts, recent technological developments make it increasingly possible to compensate for the lack of existing records.

In recent years there has been a growth of bottom-up campaigns of volunteers helping to transform satellite or other imagery into spatial data formats, a process known as crowdsourcing (Howe, 2006) which produces what some call volunteered geographic information (VGI; Goodchild, 2007). Recently attention has focused on using these crowds of volunteers to help map both physical infrastructure (such as roads and bridges) and the extent of the devastation caused by natural disasters, for example in response to crises in Haiti and Pakistan (e.g. Biewald & Janah, 2010; Zook, Graham, Shelton, & Gorman, 2010). Some of the earliest work in crowdsourcing crisis events explored wild fires in Santa Barbara, (see Goodchild & Glennon, 2010) and since then numerous other crises have been covered, mainly in the form of map mashups (see Liu & Palen, 2010). It was not until the Haiti earthquake on the 12th of January 2010 that concerned citizens, technical experts, government agencies, and non-governmental organizations (NGOs) employed Web 2.0 technologies and crowdsourcing to aid humanitarian efforts in near real-time (United Nations Foundation, 2011). After the Haiti earthquake, crowdsourcing and social networks helped fill the information gap in a timely manner. Within days of the earthquake, volunteers had used satellite imagery to trace roads, shelters, and other geographic features to make the most detailed map of Haiti available (Meier, 2011). This information played a critical role in minimizing the suffering of those affected, marking a new research frontier with respect to disaster response (Biewald & Janah, 2010).

Increasingly, these volunteer mapping efforts are not isolated, thrown-together endeavours: recent events have spurred the growth of new user communities with their own tools and standards. The volunteer mapping efforts described above were aided by the development of websites such as Ushahidi (2011) and CrisisCommons (2011) which take advantage of Web 2.0 technology, (see Graham, 2007), crowdsourcing, and VGI to rapidly develop a picture of the situation on the ground. Some researchers view this trend as a move from Disaster Relief 1.0 to Disaster Relief 2.0, in
the sense that a wide range of web mapping tools has changed how crisis information is shared and communicated. If Web 2.0 is understood to be the growth of tools to support user generated content, one can think of Disaster Relief 2.0 as people and government agencies harnessing such tools to fill the information gap in near real-time (Parry, 2011).

The motivation of this paper is to highlight how Web 2.0 technologies and their resulting data products can be used in conjunction with traditional data sources and linked to simulation efforts such as agent-based modelling (ABM) to aid humanitarian response efforts. To accomplish this task we present here the basis for a novel modelling framework which combines an agent-driven simulation with data drawn from a variety of geospatial sources, including VGI. The rationale for using ABMs is that they offer new insights into crisis response efforts: unlike other modelling approaches, ABMs can contextualize the needs and behaviours of individuals of the affected population within the post-disaster environment. ABMs allow the researcher to explore different scenario options for aid distribution, considering the costs and benefits of different efforts in terms of a number of different metrics. It is also important to remember that if we are to truly capture the situation on the ground, the ABM has to be initialized with up-to-date information products such as those derived from Web 2.0 technologies. The remainder of the paper will first provide some background on the value of linking geospatial information and ABMs in the context of humanitarian relief and how individuals behave in times of crisis (Section 2) before describing a prototype modelling framework that does so (Section 3). Section 4 highlights a sample of modelling scenarios for aid distribution. We conclude with a summary of the work thus far and discuss future avenues of research (Section 5).

2. Background and literature review

A great deal of research within the social sciences has focused on how natural disasters impact a given population and how people react to them (e.g. see Benight et al. (1999) for a review). Research has shown that both cognitive and affective responses influence people's decision-making during and after natural disasters (e.g. Loewenstein, Weber, Hsee, & Welch, 2001; Slovic, Finucane, Peters, & MacGregor, 2004; Villegas et al., 2013). Decision-making, at both the individual and the collective level, changes depending upon the nature of the crisis and the individuals involved (see Dynes & Tierney, 1994; Karanci & Acarturk, 2005). For example: earthquakes, unlike hurricanes, occur with little advanced notice. People can prepare for an oncoming hurricane and plan their evacuation or shelter accordingly, but the heterogeneous nature of the population means that people will respond to such events and warnings differently based on their knowledge, experience, and resources (e.g. Drabek, 1992 Villegas et al., 2013). An earthquake, on the other hand, is an instantaneous event, which makes planning for them more difficult and the individual's response more a function of reaction than decision (Hobfoll, 1989).

Regardless of the type of crisis, it has been shown that the greater the damage, the greater the need of the individual (e.g. Sumer, Karanci, Berument, & Gunes, 2005).

To understand how an individual might react to disruptive events and natural disasters, many researchers invoke Maslow's (1968) hierarchy of needs. This hierarchy is structured so that people seek physical resources (e.g. food and shelter), before social (e.g. social interaction), and psychological (e.g. respect from others) resources, in a hierarchical manner. This notion of basic survival has been supported by several authors (e.g. Bandura, 1977; Freedy, Shaw, Jarrell, & Masters, 1992; Hobfoll, 1989). Hobfoll (1989) and Freedy et al. (1992) both note in their case studies that after a natural disaster, an initial priority of individuals was replenishing resources basic to survival (e.g. food, shelter). In another study, Beight et al. (1999) found that disaster response teams that provided direct resources (e.g. housing, food, water) reduced subsequent distress levels of the affected population. Douty (1972) notes that after a disaster, an individual does not participate in societal activities until he has ensured the survival and well being of persons with whom he has close personal ties.

Contextualising human behaviour within space requires some sort of geographical information system (GIS) in order to identify spatial relationships. However, while the use of GIS and spatial data in emergency management is not new (see Cova (2005) for a review), applications often assume an unrealistically homogenous population or address only one instant in time. Researchers have focused on indentifying the spatial pattern of devastation (e.g. Yamazaki, 2001), carrying out risk assessments (e.g. Tralli, Blom, Zlotnicki, Donnellen, & Evans, 2005), or route planning for evacuating cities (e.g. Cova & Johnson, 2003; de Silva & Eglese, 2000), all in relatively static ways that lack the dynamic element of capturing humans interacting within and upon the environment.

Previous research has focused more on the temporal rather than the spatial aspect of disaster response, especially those simulations produced within the system dynamics modelling paradigm. For example, Kaplan, Craft, and Wein (2002) address the spread of smallpox through a population over time but not through space; Hoard et al. (2005) studied the temporal dynamics of the influx of patients into a single hospital in the aftermath of a disaster, without regard for distance. Some system dynamics models aim to capture the impact of both time and space (e.g. Fawcett & Oliveira, 2000), although the inherently aspatial nature of system dynamics models poses a challenge. Most problematically, system dynamics models lack the capacity to simulate agent-to-agent interaction, as they assume a generalized mixing of the population (Gilbert & Troitzsch, 2005). Another popular methodology is the use of discrete event simulations (DES; also known as queuing models), which also often focus on the temporal aspects of the system to the exclusion of the spatial. For example, Aaby et al. (2006) develop a DES that simulates the operations of a health delivery centre during a potential influenza pandemic, focusing on the operation of the centre in time without regard to its spatial context; Hupert, Mushlin, and Callahan, 2002 address a similar question in a bioterrorism context. These methods are well suited to the questions they address, but are not appropriate in other disaster response scenarios where spatiotemporal interactions are of critical importance.

Another widely utilized technique in the field of modelling disasters is microsimulation. Microsimulation models have been developed to explore flooding, disease transmission, and evacuation (e.g. Brouwers, 2005; Chen, 2008). While these models allow individuals to be represented and to interact with space, there is no human-to-human interaction (Gilbert & Troitzsch, 2005). However, blended approaches between microsimulation and ABMs are being developed to address these limitations (see Birkin & Wu, 2012). Blended approaches to modelling are increasingly popular in general (Ergun, Karakus, Keskinocak, Swann, & Villarreal, 2010). For example, Wein, Craft, and Kaplan (2003) link a DES with a system dynamics model to explore emergency response to a hypothetical anthrax attack. Operations research practitioners frequently attempt to merge GIS information with other methodologies to develop decision support systems (e.g. Shim, Fontane, & Ladadie, 2002). This wide range of methodologies reflects the challenges inherent in deal with crises: disasters represent the intersection between the physical and the social, and the rapidly-shifting situation on the ground is highly path-dependent but also subject to stochastic processes. Because of the difficulties involved in capturing interaction as well as stochasticity at the individual
ABMs address complex social phenomena, focusing on the interactions of actors. The goal of such models is to gain insights that will lead to greater understanding and, in some cases, better management of complex social systems (Torrens, 2010). As such a tool, ABM has the potential to offer insights into how people might react in times of uncertainty, for instance after a natural disaster, which other modelling methodologies do not allow. There are a number of reasons that ABM is particularly suited to studying crisis situations. ABMs allow for agents to exist in a spatial environment, allowing researchers to explain how populations might evacuate or the varying needs of people in different locations depending on the degree of devastation in which they find themselves. The heterogeneity of agents not only in space but also in attributes is another strength: for example women are frequently more vulnerable after a disaster than men (Nirupama & Maula, 2013), and will make choices accordingly. The ability to incorporate uncertainty is of critical importance as well, and ABM can apply stochasticity both to the environment and to agents. Friedrich and Burghardt (2007) noted that there is a great potential for the use of ABM to assist natural disasters, from helping first responders and logistical support to understanding the situation of the people affected by such events, however, such research is still in its infancy.

ABMs have often been co-opted to study problems addressed by the previously mentioned methodologies. Modellers have ‘agentised’ evacuation models, including creating spatially explicit simulations of vehicle (e.g. Thorp et al., 2006) and pedestrian traffic (e.g. Chen, Zhai, & Madey, 2010); others have linked traffic models and disease propagation (e.g. Barrett, Eubank, & Smith, 2005). By linking ABM and GIS we have the ability to model the emergence of phenomena through individual interactions over space and time (Benson & Torrens, 2004). However, there are few ABMs dedicated to studying the people who fail to evacuate, and such models tend not be overtly spatial or to study how the situation develops over time. For example, Salgado, Marchione, and Gill (2010) considered explanations for why people began looting in Chile after its 2010 earthquake, and Naqvi (2009) explored how the 2009 Pakistan floods impacted migration and local economic strength in both the affected and relatively unscathed parts of the country. Other researchers have explored the internal workings of refugee camps: Johnson, Lampe, and Seichter (2009) ran a series of simulations comparing how violence within a camp breaks out and how security personnel might respond to such unrest. In a similar quest, Anderson, Chaturvedi, and Cibulskis (2007) explored how different humanitarian assistance policies implemented by governments and non-governmental organizations impact camp refugees. To the authors’ knowledge, there are no models that combine GIS and ABM to assist humanitarian relief efforts, nor any that utilize crowdsourced geospatial data for model initialization.

The data does exist to support such an integrated effort. For example there is currently much work dedicated to providing near real-time information with remote sensing and web mapping services to carry out immediate damage assessment (e.g. Meng, Bian, Xie, & Yang, 2009). Updates from crowdsourced projects such as OpenStreetMap via application programming interfaces (APIs) could be fed into an ABM to provide more near real-time situational awareness of the spatial environment. With respect to gaining a greater understanding of people’s needs, there is also the growth in micro-tasking and geo-locating reports from crowdsourced text messages such as that of Mission 4636 (2011). In the case of Mission 4636, a free phone number was set up after the Haitian earthquake where people could text their requests for food, shelter, medical care, or other aid. Volunteers used online crowdsourcing platforms (e.g. Crowdflower and Ushahidi) to sort this information by need and priority, and then distributed it to various emergency responders and aid organizations. This information will only become more accessible and richer as time goes on, and it will be increasingly possible to use it in a simulation context.

The remainder of this paper focuses on how geospatial and social data and ABM can be combined together to aid humanitarian relief. Specifically, we focus on the devastating magnitude 7.0 earthquake that struck the Haiti on January 12th, 2010. It is estimated to have killed 230,000 people and left more than 1.6 million people homeless (BBC, 2010). Fig. 1 provides an idea of the population distribution of Haiti, with the greatest density in and around Port-au-Prince, the nation’s capital and our chosen modelling area.

3. Methodology

As discussed in Section 1, the motivation of this paper is to highlight how Web 2.0 technologies and their resulting data products can be linked to simulation efforts, specifically ABM to aid humanitarian response. To demonstrate this, we now present how various sources of information can be synthesized and used to produce projections suitable for use in the context of humanitarian response. To this end, we have created a basic agent-based model that simulates individuals in Port-au-Prince making choices in the aftermath of the earthquake. The motivation in creating the model is to produce a simple caricature of reality (Axtell & Epstein, 1994) and explore a humanitarian crisis event.

The model takes as input data products derived from a diverse range of crowdsourced or VGI data: geographic information about the population density, relative level of devastation, existing transportation network, and location of aid centres, along with a series of parameters that describe the environment, as shown in Table 1. While some of these parameters are of interest in the sense of testing effective aid distribution (e.g. amount of food or energy from food), others are provided in this accessible way to allow other researchers to use their own evaluations for the cost of movement or the maximum possible crowd density. As output, the simulation produces a map showing the movement of individuals throughout the environment and the spread of information about aid availability, as well as graphs tracking agent activity and the utilization of different aid centres over time. At the end of the simulation, the model reports a series of statistics, which capture the overall health of the population as well as the final status of the aid centres. Internally, the model consists of a number of modules that capture the physical and social processes that impact aid distribution.

The model itself is loosely coupled to GIS and is written in Java, utilizing and extending the MASON simulation toolkit (Luke, Cioffi-Revilla, Panait, Sullivan, & Balan, 2005) as well as its recently released GIS extension, GeoMASON (Sullivan, Coletti, & Luke, 2010). MASON is primarily used for its scheduler of model actions, its visualization tools for displaying model information, and importation functionality for GIS vector and raster data. For interested readers the source code and data are available at the project website (http://www.css.gmu.edu/haïti). We do this for the sake of replication and docking, because if a model cannot be meaningfully compared to other work, its credibility is unverifiable and its ramifications necessarily proscribed (Axtell, Axelrod, Epstein, & Cohen, 1996).

3.1. Data preparation

In order to build the artificial world in which our simulation exists, the simulated environment needs to reflect the situation on

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1 Note that Haiti has an estimated population of 9,719,932 (CIA, 2011).
the ground after the earthquake. Several datasets are needed to do this and these have been drawn from a range of sources. The model combines and utilizes both raster and vector data structures into a single simulation, utilizing both ESRI grid and shapefiles with a range of different resolutions. These data capture information about the target location, an 8 by 6 km area around Haiti’s capital and most densely populated city, Port-au-Prince. The study area and data used within the model is shown in Fig. 2.

First, to initialize the population of agents in a way that realistically parallels the distribution of individuals throughout the city, we needed an estimate of population distribution over the study area: for this we use population counts from the 2009 LandScan (2011) dataset as shown in Fig. 2B. LandScan data divides the world into roughly 1 km by 1 km squares and assigns a population count to each cell (Cheriyadat, Bright, Bhaduri, & Potere, 2007). Such a data source is useful for estimating baseline populations where census data is missing (as is often the case in less developed countries). When using this data to initialize our agents, we assume that the agents are evenly distributed throughout the 1 km by 1 km area, excluding the parts of the environment that are determined from other GIS data to contain water or similar obstacles. Based on this information and methodology, the simulation is initialized with approximately 1.3 million agents.

It was also necessary to determine the level of devastation throughout the city in order to determine where need would be greatest (e.g. Sumer et al., 2005). Information about the devastation or damage levels was taken from G-Mosaic (2010) which released satellite derived damage reports on the 16th of January, 2010, only 4 days after the earthquake. G-Mosaic’s classification assesses the damage at a location using a series of qualitative levels: totally destroyed, collapsed structures, visible damage, intact, and unclassified areas. The geographic pattern of destruction as described by this classification is shown in Fig. 2A. G-Mosaic presents its data in a number of smaller maps, so it was necessary to stitch the images together in order to represent the entire study area.

In order to understand the way individuals could move through the area, we needed an understanding of the transportation network. The series of roads that existed in post-quake Haiti was taken from a VGI repository. We used vector road lines sourced from OpenStreetMap, created on the 15th of January, 2010, via the Geocommons (2010) Haiti Data repository. These roads are highlighted in Fig. 2C. Finally, the aid centre locations are given to the simulation by a text file and the environmental variables are either passed to the simulation by the user or taken to be the default values shown in Table 1.

### Table 1: Parameters of the model.

<table>
<thead>
<tr>
<th>Type</th>
<th>Parameter</th>
<th>Description</th>
<th>Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Agents</td>
<td>Energy level</td>
<td>Set at model initialization based on location of the agent and level of destruction. The greater the destruction, the lower the energy value</td>
<td>1000–2000</td>
</tr>
<tr>
<td></td>
<td>Energy_to_Stay</td>
<td>Energy expended staying at home</td>
<td>0–20</td>
</tr>
<tr>
<td></td>
<td>Energy_to_Walk_Paved</td>
<td>Energy expended walking on paved road</td>
<td>0–20</td>
</tr>
<tr>
<td></td>
<td>Energy_to_Walk_Unpaved</td>
<td>Energy expended walking on unpaved roads</td>
<td>0–20</td>
</tr>
<tr>
<td></td>
<td>Re-evaluate Interval</td>
<td>How often (in terms of ticks) does the agent re-evaluate its activity?</td>
<td>0–10</td>
</tr>
<tr>
<td>Environment</td>
<td>MaximumDensity</td>
<td>Maximum number of agents per 100 m²</td>
<td>0–20</td>
</tr>
<tr>
<td>Centres</td>
<td>FoodLevel</td>
<td>Amount of food initially available at the centre</td>
<td>0–1000</td>
</tr>
<tr>
<td></td>
<td>Energy_From_Food</td>
<td>How much energy does the agent receive from one unit of food</td>
<td>0–1000</td>
</tr>
</tbody>
</table>

3.2. Model structure

The model implemented here is an ABM that breaks down the system being studied into an environment and considers two different types of actors: Aid Centres (called Centres) and Agents, discussed in Sections 3.3.1 and 3.3.2, respectively. The environment in which the actors exist is a physical space, represented here by a grid with a resolution of 100 m². Fig. 3, provides an overview of
the key processes within the model. These will be further expanded below.

When constructing a model, it is necessary to select a time step that is appropriate for the processes being simulated. This time step can vary tremendously: the step may attempt to capture long-term dynamics, as in yearly-updating models of demographic change (e.g. Wu & Birkin, 2012) or urban growth (e.g. Magliocca, 2012), or it may be applied to an extremely rapidly-changing system which needs to be updated every second, as in the case of some pedestrian models (e.g. Torrens, Li, & Griffin, 2011). While the notion of time in the model is both abstract and highly adjustable, a tick of the simulation could be considered to be about 5 min of real world time. This unit of time was selected in light of the granularity of time associated with individuals’ decision-making, movement, and energy expenditure.

3.3. Types of agents

It is important to note that the agents in this model are extremely simple in terms of both agent decision-making and communication. This simplicity is intentional: we are building a baseline model which can be extended in future research, some examples of which are suggested in Section 5. The primary strength of ABMs is as a testing ground for a variety of theoretical assumptions and concepts about human behaviour (Stanilov, 2012). By keeping the initial behaviours and assumptions simple, we can more clearly identify the underlying dynamics that give rise to the system-level properties. In a sense, our model is similar to the zero-intelligence traders model (Gode & Sunder, 1993) used in economics, whereby agents with nothing more than a budget constraint and a prohibition against trading at a loss, replicate the demand and supply curves of ‘real’ markets. With the zero-intelligence model as a base, it is possible to compare complex models that tweak its simple assumptions to better emulate the patterns of trading seen in the real world (e.g. Cliff & Bruten, 1997). Such simple models provide a basis for more complex models, while ensuring that the dynamics are correctly understood and attributed. As such they form the foundation for future research without the risk of confounding our results.

3.3.1. Centres

Centres represent the aid distribution points in the simulation. As an object, a Centre is both a location and an actor. It is a location in that it cannot move, and in that two Centres cannot share one location. Centres are actors in that they are endowed with a certain amount of food that is distributed to Agents that enter the Centre’s grid point at a rate of one unit of food per Agent. Centres can only distribute as much food as they have on hand, so once they run out of supplies, Agents are turned away. While Centres can be resupplied throughout the simulation, in the following runs, Centres are given an initial allocation of food and never resupplied. The purpose of the Centres is to provide physical resources to the affected population and, thus meeting one of the basic survival needs of the target population, as discussed in Section 2.

3.3.2. Agents

Each Agent represents an individual capable of making decisions, communicating with its peers, and moving around the environment. They are motivated by Maslow’s (1968) hierarchy of needs, as discussed in Section 2, in the sense that they seek resources basic to survival (e.g. food) to the exclusion of all other activities. Agents have a personal energy level and knowledge of their environment, including the location of their own home and are potentially aware of the Centres existence (as discussed below).

The most important attribute for any individual Agent is its energy level, which reflects in an abstract fashion the health of an Agent. It is the goal of Agents to maximize their energy levels over the course of the simulation. Agents burn energy with time (every tick) at a rate proportional to the activities they are pursuing (Table 1), emulating a metabolism of sorts. When an Agent receives food from a Centre, it experiences an increase in energy as it ‘consumes’ the food. If a given Agent’s energy falls below zero, the Agent...
is said to be dead and it is removed from the simulation. It does not leave behind any 'body' on the landscape, so the movement of other Agents around its former position is not impeded. Agents whose homes are located in areas that have suffered extreme levels of destruction are assumed to begin the simulation with fewer resources and therefore have lower energy than Agents from relatively intact neighbourhoods, reflecting the varying needs of the heterogeneous population. The Agents initial energy levels are given in Table 2.

With respect to Agent decision-making, in pursuit of its goal of maximizing energy, the Agent can choose among a number of actions, including walking to various Centres or deciding to stay home. Its choices are predicated upon the body of knowledge it maintains regarding the presence of aid supplies at various Centres and its understanding of the road network. The Agent’s rule based decision tree is depicted in Fig. 4, and essentially seeks to determine the optimal energy use of any action. As even the act of staying home requires a certain amount of energy, it is not a given that staying home will be the energy-maximizing choice. Instead, an Agent will consider whether any of the Centres it knows to be stocked with supplies are close enough to make a trip to them worthwhile, which is to say that the travelling costs are lower than the projected energy increase from a unit of food. If the Agent finds any Centres where the energy boost from food outweighs the cost of making the trip there and back, the Agent selects the Centre associated with the greatest net energy increase and moves along the road network to that location. Agents constantly reassess their choices, so that if an Agent en route to Centre A is told of Centre B’s new supply of food, it calculates whether the cost from its current location to Centre A and then home is less than the cost from its current location to Centre B and home. As such, Agents respond meaningfully to new information and are constantly replanning their actions.

<table>
<thead>
<tr>
<th>Destruction level</th>
<th>Energy level of the agents</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intact buildings, no damage, no data</td>
<td>2000</td>
</tr>
<tr>
<td>Visible damage</td>
<td>1600</td>
</tr>
<tr>
<td>Moderate damage</td>
<td>1200</td>
</tr>
<tr>
<td>Severely damaged</td>
<td>1000</td>
</tr>
</tbody>
</table>

Fig. 3. Flow diagram of the key processes within the model.
Agents plan their movement based on the road network, but the mental maps individuals associate with their environment may be in conflict with the post-disaster infrastructure. As such, Agent movement is constrained by the real road costs. Individuals plan their paths using an A* algorithm on the road networks they understand to exist, but the quality of the roads impacts the amount of energy that is burned by Agents in moving over them. Agents are assumed to move at a speed of approximately 100 m per tick. However, in situations where Agents are attempting to move into a location where the maximum density is already reached, the Agent cannot move forward and must stay in its current location. While there may be multiple Agents in one location, Agents cannot move into spaces that are already occupied by too many other Agents, and must wait until other Agents move away and the local density lessens.

The knowledge Agents have of food availability is a function of Agent rumour-spreading. Agents maintain a list of Centres that have been supplied with aid, and are assumed to pass this information along to individuals in the same location and within a small radius around them (i.e. hearing about food availability via word of mouth). At model initialisation when a Centre is resupplied, the Agents in its immediate vicinity ‘witness’ this and gain knowledge of the availability of food, which they immediately begin to communicate to others via word of mouth. Agents do not strategically limit information-sharing, never lying or omitting information by accident. It is important to note that Agents do not pass information that certain Centres have run out of food, so that a rumour about a Centre being resupplied may be passed along even after that Centre’s stocks have been depleted.

Agents, with their extremely basic bodies of knowledge and drives, are a fundamental unit which can be modified in the future to incorporate concepts of bounded rationality, social obligation, strategic communication, the impact of emotion on decision-making, or any number of cognitive management systems, to name but a handful of obvious extensions (see Kennedy, 2012). By keeping Agents simple here, it will be easier to compare the value of incorporating more data, versus building a richer cognitive model, versus pursuing both courses in future work. Our fundamental assumption – that individuals want to survive and will do so as best they know how – allows tremendous latitude for future research to explore behaviour and decision-making in crisis scenarios.

3.4. Model output

The model outputs a number of comparative statistics at the end of a simulation, specifically the number of Agent deaths, the number of units of aid that went undistributed, and the cumulative amount of energy of all living Agents. We present the results here in normalized terms, reporting the ratio of deaths to population and the ratio of energy to the number of surviving individuals. The significance of the ratio of deaths is obvious, while the number of undistributed aid packages is meant to measure how effective the distribution effort was from the perspective of the aid organization. The ratio of energy to survivors is a notional measure of the ‘population health’; it attempts to distinguish a population in which everyone survives but no one is particularly healthy from a population in which a few people die but the remaining population is relatively healthy.

4. Simulation results

We present here our efforts to verify the correct functioning of the model as well as our comparison of the relative effectiveness of three different Centre setups. In every case described here, the model was run for 500 steps, long enough for the Agents to find out about the Centres and set out toward them.

4.1. Sensitivity testing

An initial parameter sweep was run to verify that the simulation was constructed correctly and that the relationships among variables were reasonable. For brevity, we present only a subset of these parameter sweeps here. To highlight the sensitivities of the model, we explored the impact of varying the energy costs per activity. The default values for energy usage are based on approximate real caloric values relative to the activity and time step: sensitivity is tested by significantly varying the values around the default values. The parameter sweep tested the impact of varying the cost of staying in place from 0.15 to 1.5 to 5; the cost of walking on paved roads from 0.5 to 5 to 15; and the cost of walking on unpaved roads from 0.6 to 6 to 20. The real caloric values are based on the calories expended per hour in common physical
activities (U.S. Department of Health, 2005). All other parameters were kept consistent with the default values shown in Table 3.

The results of the parameter sweep indicate a number of interesting and reasonable dynamics. As the cost of staying in place increased, the relative cost of going to the Centres in search of food lowered, resulting in much higher rates of food consumption as shown in Fig. 5. Holding the cost of staying in place high, more food was consumed when the cost of walking was relatively cheap compared to when walking was relatively expensive. The normalized energy values tell a similar story: as the cost of staying increased, the normalized energy dropped dramatically as shown in Fig. 6. When the cost of unpaved walking was at its cheapest, the final cumulative normalized energy was higher. Even when unpaved walking was cheap, the cost of staying dramatically impacts the system energy levels. The number of deaths at the end of the simulation follows this pattern, with low costs resulting in vanishingly few deaths and the highest costs seeing almost the entire population die off, as shown in Fig. 7. In short, the relative costs of activities encourage some activities over others, and the default balance of costs is appropriate. We can conclude from these sweeps that the model functions in a reasonable fashion, and verify it as performing as expected.

4.2. Comparison of different centre distributions

As the parameter sweep above has shown, the model is sensitive to the costs of movement. As discussed in Section 2, Benight et al. (1999) noted that providing direct resources (e.g. food) after a disaster had a significant impact on the levels of distress of the population. In the following scenarios, we attempt to investigate how the placement of aid centres in times of crisis impacts the population at large with regard to food consumption, specifically whether the locations of aid centres are accessible to the population at large. All of the parameters of the model are set to the default values (Table 3), and the only variation is the location of the Centres. Three Centre location setups were compared against one another as enumerated below, and their performance on the various statistics is compared. The locations of the Centres in each setup were selected by the researchers not to identify suggested locations, but to provide a sense of the range of outcomes that arise as a result of their placement.

- **Random**: In the first setup, four Centres are placed along the road network. This was the setup upon which the parameter sweep was run (Section 4.1), and is thus referred to here as the Random setup as shown in Fig. 8A.
- **Good**: In the second setup, Centres are located near the highest-need areas. They are on the road network and spread throughout the environment to promote access, as shown in Fig. 8B.
- **Bad**: The third setup has the Centres in inaccessible, low-population density areas far from the road network and not as grievously damaged by the earthquake. Information does not travel as well in low-density areas, so the positioning of these Centres to a degree impedes the flow of information about them. The setup is shown in Fig. 8C.

The three types of Centre distributions scenarios were each run 50 times, producing the data shown in Table 4. As expected, the results generated by the ‘Random’ scenario match the results associated with the parameter sweep runs dedicated to the default parameters, as they utilize all of the same parameter values and data. The performance of the different Centre distributions on the different metrics produced a number of interesting dynamics as shown in Table 4, and the standard deviations associated with each of the measurements are extremely low, suggesting that the results are characteristic of the scenarios. On arguably the most important metric, the death rate, the ‘Random’ setup performed best among the options, having an average loss of 0.14% and a rate...
that ranged between 0.11% and 0.17%. This is somewhat surprising, given that the ‘Good’ setup was designed to target the most vulnerable populations, but the ‘Random’ and ‘Good’ setups managed to distribute almost the same amount of food. While the ‘Good’ setup distributed, on average, only one fewer parcel of food per run of the simulation, it saw several thousand more deaths. This is despite the fact that the total amount of normalized Agent energy left at the end of the simulation is approximately constant across all three scenarios. Somehow, the ‘Random’ scenario distributed the same quantity of food in a better fashion.

This is not to say that the ‘Good’ scenario performed poorly; compared to the ‘Bad’ scenario, the ‘Good’ scenario distributed more food and saved more lives. The average ratio of death for the ‘Good’ scenario is less than the lowest ‘Bad’ death rates. There is a reasonable quantity of food left over at the end of the ‘Bad’ scenario – why, then, do Agents not consume it and lower the death rate? The answer to these puzzles lies in Agents making the choice of whether or not to seek out aid: we should perhaps frame the question not as one of which Centres did the most good, but which did the least harm? Because Agents make their choices based on how much energy they believe the journey will take, ‘unexpected’ phenomena such as washed-out roads and huge crowds can easily turn the trip from a net gain to a net cost. An Agent may fight its way through a large crowd only to find that the Centre, to which it has travelled at such cost, has run out of aid packages. In these cases, the aid centre may have done more harm than good. In the case of the ‘Random’ scenario, then, the inconvenience of some Centre locations dissuaded Agents from attempting to make the trek, and the limited spread of information kept some in the dark. The central locations of ‘Good’ Centres meant that Agents who derived little benefit from making the trip versus staying home found out about the Centres and decided to set out.

A similar dynamic explains the seemingly strange trend of higher death rates being associated with greater system-level health, or higher normalized energy rates. While more Agents died, the Agents who survived are much healthier than their peers in the other setups. As such, a model evaluated only on the basis of system-wide health might suggest that one setup was superior, even if it resulted in many more deaths than the models against which it was being compared. The results reflect the importance of choosing Centre locations wisely and considering a number of different metrics of success.

5. Summary and outlook

This paper has demonstrated how GIS and ABM can be utilized to explore humanitarian relief at the individual level after a natural disaster, such as an earthquake. Our framework presented here harnesses crowdsourced, volunteered geographic data as well as other publicly accessible information to build realistic and time-sensitive agent environments. The model demonstrates how such data can be used to initialize agents, their needs, and their environments, and how through a simple information dispersal mechanism and decision-making process we can emulate the behaviour of individuals in a crisis context. We consider this an important aspect of such efforts: natural disasters are times of great uncertainty, and it is difficult to predict beforehand how people will

![Fig. 7. The number of agent deaths at the end of the simulation runs.](image)

![Fig. 8. Different aid centre positioning where the blue stars represent the centres. (A) Random; (B) good, and (C) bad. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)](image)

<table>
<thead>
<tr>
<th>Setup</th>
<th>Avg. death rate</th>
<th>Death rate range</th>
<th>Std. dev. death rate</th>
<th>Avg. final norm. system energy</th>
<th>Std. dev. final norm. System energy</th>
<th>Avg. total food left</th>
<th>Std. dev. total food left</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>0.0014</td>
<td>(.0011, .0017)</td>
<td>0.0001</td>
<td>793.1</td>
<td>0.5</td>
<td>19.0</td>
<td>1.52</td>
</tr>
<tr>
<td>Good</td>
<td>0.0036</td>
<td>(.0033, .0043)</td>
<td>0.0002</td>
<td>795.5</td>
<td>0.4</td>
<td>20.2</td>
<td>2.08</td>
</tr>
<tr>
<td>Bad</td>
<td>0.0044</td>
<td>(.0038, .0049)</td>
<td>0.0002</td>
<td>798.3</td>
<td>0.4</td>
<td>25.5</td>
<td>2.03</td>
</tr>
</tbody>
</table>
react to such events. By using ABMs we can explicitly explore potential agent behaviours and aid our understanding of processes and their consequences. Our paper is an initial step towards this larger research agenda.

In the future, such a model, once thoroughly developed and validated, could be of potential use as a decision support tool for humanitarian relief. For example, it may be possible for a relief worker to create such a model of an affected area in near real-time, incorporating the available data. With new sources of information being provided by Disaster 2.0-focused organizations like the Humanitarian OpenStreetMap Team, Mission 4636, Crowdflower, and Ushahidi, as well as other Web 2.0 platforms such as Twitter, Flickr, and Facebook, it will become increasingly possible to rapidly and accurately gain an understanding of the situation in the target area. Such data would allow one to assess not only the regional damage, but also security concerns and the needs of the affected population. Need and priority-tagged information could help us inform agent behaviours through content analysis. Moreover, if social networks or communication between agents is known, and agents are endowed with mobile phones or radios, various methods for information diffusion could be explored rather than relying on word of mouth as in the current model. Through a geographically explicit agent-based model, we could map future trajectories of the system to see what might happen. Below, we sketch out a framework that, once fully developed, has the potential to be utilized by responders or citizens to explore ‘what-if’ scenarios as information becomes available.

To give a sense of the kind of system that could rapidly incorporate new information, Fig. 9 sketches out a possible structure for a framework where the ABM has the capability to evolve in the presence of additional geospatial and social information. This would allow the ABM to make use of incoming information and to adjust to the current (or predicted) conditions in the area of interest. This continuously evolving loop takes us from the original data for a region, which is used to build and initialise the initial model, and dynamically incorporates the new information into the model as it becomes available. Moreover, the model could identify areas where more data is needed. This will require ingesting data from a variety of sources (for example, automatically accessing databases via APIs) and transforming them into an ABM with a normalized and therefore comparable structure. Such data could include:

- Spatial data (e.g. roads, infrastructure, levels of destruction and the built environment) accessed from authoritative datasets (e.g. derived from remotely sensed imagery), or volunteered data (e.g. OpenStreetMap or Ushahidi) to provide accurate descriptions of the physical environment.
- Social data (e.g. population information or events affecting a society), also accessed through authoritative datasets (e.g. census data, agency reports) or other open-source information (e.g. news feeds, Twitter), used to provide researchers with an understanding of the social–cultural conditions in the field. Moreover, they could be used to build social networks, which give insight into the interactions amongst individuals.

The utility of ABMs within a crisis context does not stop with aid distribution; ABMs can also be used to forecast the development of local circumstances after the event. For example, Haiti has recently been affected by outbreaks of cholera, civil unrest against United Nations peacekeepers, and flooding. Applications utilizing GIS, ABM, and other data sources (such as social media) could address civil violence (similar to the work of Epstein, 2002), rebuilding the city using modified urban growth models (similar to the work of Jantz, Goetz, Donato, & Claggett, 2010) or monitor the spread of diseases (e.g. Eubank et al., 2004). This paper represents a first step and basis for using data-rich ABMs in humanitarian response capacities, and moreover highlights the opportunities that exist for combining volunteered geographical information with other crowdsourced data to provide greater situational awareness.

**Fig. 9.** Data gathering and modelling cycle for a humanitarian agent-based model.

**References**


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