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An agent-based modeling approach applied to the spread of cholera

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ABSTRACT

Cholera is an intestinal disease and is characterized by diarrhea and severe dehydration. While cholera has mainly been eliminated in regions that can provide clean water, adequate hygiene and proper sanitation; it remains a constant threat in many parts of Africa and Asia. Within this paper, we develop an agent-based model that explores the spread of cholera in the Dadaab refugee camp in Kenya. Poor sanitation and housing conditions contribute to frequent incidents of cholera outbreaks within this camp. We model the spread of cholera by explicitly representing the interaction between humans and their environment, and the spread of the epidemic using a Susceptible-Exposed-Infected-Recovered model. Results from the model show that the spread of cholera grows radially from contaminated water sources and seasonal rains can cause the emergence of cholera outbreaks. This modeling effort highlights the potential of agent-based modeling to explore the spread of cholera in a humanitarian context.

Software availability

Software Requirements: Java, MASON, GeoMason
Programming Language: Java
Program availability and cost: Free, GPL. http://css.gmu.edu/Cholera/
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1. Introduction

Cholera is an intestinal disease caused by the bacterium *Vibrio cholerae*, which colonizes the human intestine (Bertuzzo et al., 2010; Sack et al., 2004). The disease is characterized by diarrhea and severe dehydration. The main transmission mechanism for cholera is by drinking water or eating food contaminated by *V. cholerae*, which enters the environment via feces (stools) from infected people. Pandemics of cholera have been seen throughout the world from the Indian sub-continent, Africa, Europe and the Americas (Codeço, 2001; Ali et al., 2012). Even though cholera itself is both preventable and treatable via the treatment of raw sewage or by providing clean drinking water, using oral cholera vaccines or once infected using rehydration therapy, it remains a health hazard in many developing countries where such care or prevention is not possible. It is extremely difficult to obtain the actual numbers of cases and subsequent deaths per year due to under or no reporting (Ali et al., 2012), but it is estimated that there are between 3 and 5 million cholera cases and 100,000–150,000 deaths per year, mainly in developing countries (Clemens, 2011; Longini et al., 2007; Sack et al., 2004; Waldor et al., 2010). Once cholera arrives into a new region, either carried by an infected person or by contaminated water or food, three different scenarios might arise. The first is that there is no outbreak; the second is an outbreak which is then followed by few waves of outbreaks. This leads to epidemic cholera as the population has little immunity (Clemens, 2011). In the third scenario, an outbreak occurs which is then followed by subsequent out-breaks that have a persistent seasonal pattern (Codeço, 2001). The later is known as endemic cholera as seen in the Ganges Delta (e.g. Clemens, 2011).

While cholera has mainly been eliminated in regions that can provide clean water, adequate hygiene and proper sanitation (Waldor et al., 2010), cholera is an acute problem in Africa. In particular when related to refugee camps as they often suffer from poor sanitation and low per capita availability of water (see Siddique, 1994; Swerdlow et al., 1997; Heyman et al., 1997; Toole and Waldman, 1997; Cronin et al., 2008). For example, 10,000 Rwandan refuges died from cholera in 1994 (Waldor et al., 2010). Within this paper, we focus on one such camp complex: the Dadaab refugee camp, located near the Kenya–Somalia border in the North Eastern Province of Kenya as shown in Fig. 1. This camp complex

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hosts nearly 0.5 million of refugees (UNHCR, 2012) with a high influx of new refugees coming from Somalia due to drought, famine, and violence. The camp has poor sanitation and housing conditions with frequent incidences of cholera outbreaks (see UNHCR, 2011b) along with other diseases (e.g. measles). In the remainder of this paper, we first review past attempts to model cholera and the utility of agent-based models to explore such an issue (Section 2). In Section 3, we present our conceptual model before presenting some model results in Section 4. Finally we summarize the paper and identify areas of further work.

2. Background

Our understanding of how cholera spreads and infects people relates to some of earliest work with respect to the spatial analysis and disease outbreaks. Snow (1855) used mapping to explore the association between water contamination and the risk of cholera in the 1854 London cholera outbreak. This analysis not only lead to the foundation of modern epidemiology (Longley et al., 2010) but also showed the importance of space when exploring the spread of the disease. Snow's work has proved to be an inspiration of other studies of cholera, all of which extends his basic research. For example, Geographical Information Systems (GIS) have been used to identify the environmental preconditions (e.g. rainfall and temperature) leading to the outbreak of cholera (e.g. Fleming et al., 2007) or developing cholera prediction models with several months lead time from remote sensed images and climate models (e.g. Lobitz et al., 2000; Pascual et al., 2008; Reiner et al., 2012; Jutla et al., 2013).

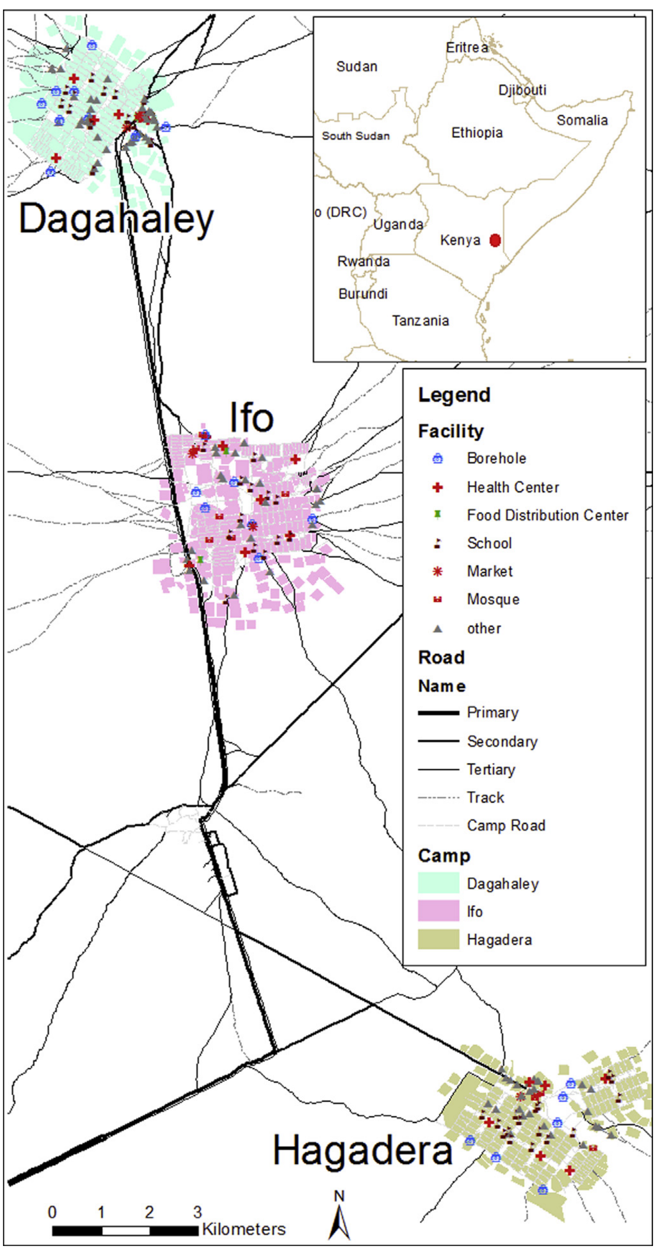


Fig. 1. The Dadaab refugee camp and its physical infrastructure.

Although cholera has a long tradition of being mapped and modeled using spatial analysis techniques (e.g. Oseia et al., 2010), modeling the propagation and the spread of the disease on the human population has had a much briefer history. Several cholera models exist, which use aggregate mathematical models utilizing differential equations (e.g. Capasso and Paveri-Fontana, 1979; Codeço, 2001; Longini et al., 2007; Bertuzzo et al., 2010, 2011; Chao et al., 2011; Tuite et al., 2011). Many of the more recent cholera models have been spurred on by the recent outbreaks of cholera in Haiti. For example Tuite et al. (2011) developed a spatial interaction model on the probability of cholera transmission using the Susceptible-Infected-Recovered (SIR) model at the meta-population level in order to calculate what percentage of the population needed to be vaccinated to stop the spread of cholera. The notion behind such models is that if one can detect the rate in the number of infections at the start of a cholera outbreak, one could provide information with respect to the spread of cholera in the future (Mukandavire et al., 2013).

While such styles of models have proved useful, they have also been criticized by researchers. For example, Epstein (2009) writes that such models are ill-suited to model complex natural-human systems. This relates to the notion that such models do not incorporate direct contact between individuals or their environment, and too often assume uniform mixing (Eubank et al., 2004), which is not the case as people interact with each other in many different ways (Crooks and Heppenstall, 2012; Filatova et al., 2013). Moreover, they treat people as aggregate individuals, missing the heterogeneity of the human population and key individual based behaviors. By focusing on heterogeneous individuals operating over different social and geographical spaces, we can capture a fundamentally different view of the disease dynamics (Levin et al., 1997).

Agent-based models (ABMs) therefore offer an alternative to classical mathematical models or discrete choice models (Bithell et al., 2008) as compared to other modeling approaches (e.g. system dynamics, bayesian networks) ABMs allow us to focus on the dynamic interactions between individuals and their impact on the system under study (Kelly et al., 2013). Moreover, Kelly et al. (2013) note that ABMs are particularly suitable when the purpose of the model is for developing an understanding of the system under investigation, where assumptions about processes and interactions can be explored through simulation. Also by linking agent-based models to GIS allows us to explore and understand the complexity of disease transmission over space (Perez and Dragicevic, 2009). It has already been shown that the landscape and the sharing of resources have an impact on disease transmission (e.g. Nunn et al., 2014). For these reasons, ABM within epidemiology has been growing, and applications range from studying dengue fever (Lourenço and Recker, 2013), foot-and-mouth (Dion et al., 2011), hepatitis (Ajelli and Merler, 2009), influenza (Rao et al., 2009), malaria (Linard et al., 2008), measles (Perez and Dragicevic, 2009), mumps (Simoes, 2012), smallpox (Epstein et al., 2002), swine flu (H1N1, Epstein, 2009), tuberculoses (Patlolla et al., 2006) etc. Little attention however, has been focused on using ABM for cholera, with the exception of the work of Augustijn-Beckers et al. (2011) which modeled the spread of cholera within a small district within the city of Kumasi, Ghana. However, our model differs in two aspects compared to this model. First, we do not use a SIR model but rather a Susceptible-Exposed-Infected-Recovered (SEIR) model. Secondly, we focus on refugee camps rather than a small area where water becomes contaminated via a refuse site. Moreover, compared to the mathematical models presented above, our model explores how specific individuals develop cholera rather than a probability of getting it. Additionally, with respect to refugee camps there has been little work carried out using ABMs. For example Johnson et al. (2009) explored violence within camps and how military personnel might respond to it. While Anderson et al. (2007) developed an abstract model that explored how humanitarian assistance policies implemented by governments and non-governmental organizations impact on camp refugees. Our model on the other hand is spatially explicit and models people's daily activities in a refugee camp, a disease is then added into the system allowing us to observe what happens.

3. Conceptual model

In the following section, a description of the model is given based on the Overview, Design concepts, and Details (ODD) protocol by Grimm et al. (2006). Full implementation details including a more detailed ODD, source code, model results and models for each of the experiments are available at www.css.gmu.edu/cholera.

3.1. Overview

3.1.1. Purpose

The purpose of the model is to explore the spatiotemporal dynamics of the spread of cholera, which is caused by the interaction of human (host) with their environment and significantly extends the basic model of Hailegiorgis and Crooks (2012). As discussed above, we utilize an ABM for this purpose as such an approach is most suitable for a developing an understanding of the system under investigation where assumptions about processes and interactions can be explored in a dynamic environment (Kelly et al., 2013). As with all models, however, a number of simplifying assumptions have been made to covert the complexities of reality into a problem which can be modeled (Batty and Torrens, 2005), which we detail below.

3.1.2. State variable and scales

The model focuses predominantly on the spatiotemporal spread of cholera within the Dadaab refugee camp. To gain a greater understanding of the dynamics of cholera transmission, agents' daily routines are incorporated into their behavior. We represent the environment using geo-referenced spatial data. Fig. 2 shows the Unified Modeling Language (UML) diagram of the model.

The main agent in the model is the refugee agent who represents an individual refugee who lives in the Dadaab refugee camp. A refugee agent has family and a fixed home location. Agents of the same family cooperate and share resources. Agents are instantiated with different attributes that contribute to their heterogeneity. Agents differ in their personal characteristics (e.g. age, sex), social ties (e.g. number of family members and friends), their body immunity type (symptomatic and asymptomatic, Section 3.3.3.3), and goals and priorities (Section 3.3.3.1). Behaviorally, agents are mobile and purpose-oriented. They determine a specific activity (goal) at a given time, depending on their priorities, and move towards it to fulfill their goal. In this model, we relate activities with facility locations. We consider nine types of activities: location of residence (i.e. homes), school, water point, religious center, market, food distribution center, health center, latrine, or lastly the agent's friend or relative houses within one of the camps (this is discussed further in Section 3.3.3).

All refugees are considered as susceptible hosts to cholera as they are myopic agents who do not have the knowledge to differentiate between clean and contaminated water. Hence, they can easily be exposed to cholera infection if they ingest contaminated water. For simplicity, we did not specifically model cholera bacteria as an agent, rather we use water flows and contamination as a proxy to model the spread of cholera (Section 3.3.3).

The other component of the model is the environment, which is a representation of the Dadaab refugee camp. It has a spatial extent of 13.5 km by 25 km with a spatial resolution of 90 m by 90 m. The spatial resolution is equivalent with a typical average distance that human can travel in a minute. The spatial extent covers all of the three camps sites (i.e., Dagahaley, Ifo and Hagadera) located around the town of Dadaab. The environment encompasses field units (i.e. cells), camp boundaries, homes (e.g. tents), facilities, infrastructure (e.g. roads), and elevation. The field unit is the main unit of the environment in which all processes of the model take place. A field unit may hold up to 100 houses but can only hold a single facility (e.g. a hospital or school). All roads (primary roads, secondary roads, feeder roads, and trails) are represented as the same type.

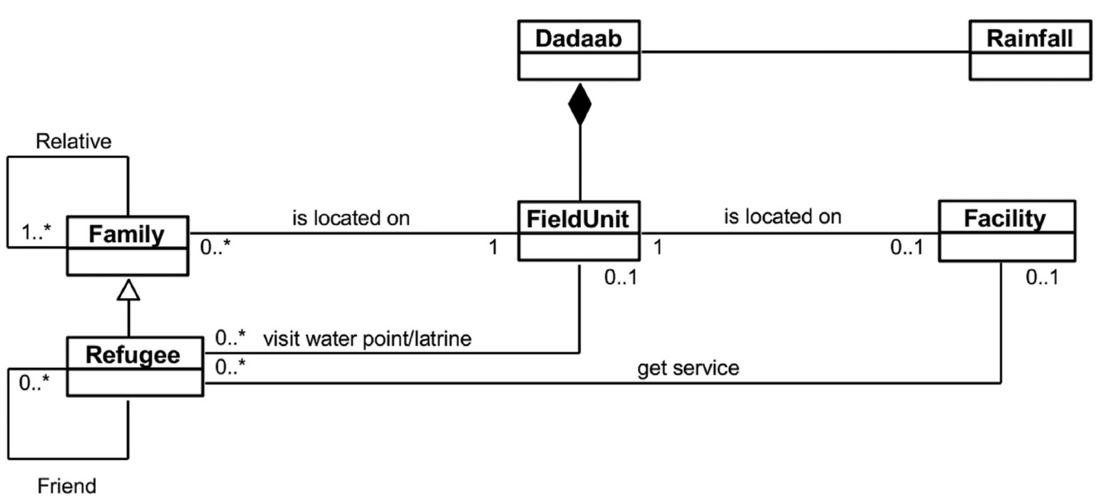


Fig. 2. High level representation of the model using a UML diagram.

There is no cost or preference on the types of the road the agents chose to navigate between activity locations; however, the roads do have a capacity that constrains the flow of traffic (i.e. agents). This is represented as 'crowd parameter', in the sense that the road can only be occupied by a given number of agents. If the road ahead is crowded, agents will stay where they are and wait until space becomes available.

There are four temporal resolutions within the model: minute, hour, day, and week. Each step of the simulation represents a minute. At each initialization of the model, the clock starts at midnight (0 min, 0 h, 0 day, 0 week). Agents' activities and decision-making processes are impacted by this clock. For instance, every day agents attempt to fulfill their goals and spend the night in their homes.

3.1.3. Process overview and scheduling

In each time step, each agent makes decision to stay where they are or move to their goal based on their priorities (e.g. needing food or water, to attend school etc.).[1] Agent movement from home to a goal is determined by the time available and their success at the goal as shown in Fig. 3. Each agent moves towards its goal by first selecting the nearest road and then plans its route using an A* graph-based shortest-path algorithm (Hart et al., 1968). Since an agent is constrained by time, the success of the agent to accomplish its goal is not guaranteed. If an agent is successful and reaches its goal, the agent might return to its home or stays at his goal (e.g. school) for a specific amount of time in order to accomplish its activity before the agent returns to its home (e.g. case 1). If the agent is too late to accomplish its goal, the agent will return home before reaching its goal (e.g. case 2). In some instants, an agent might consider choosing another goal before going back to its home (e.g. case 3). In the current version of the model, this will only happen when the agent fails to collect enough water from their nearest water point (e.g. the water point has run out of water) and the agent is therefore forced to search for other water points to achieve its goal. Goal selection and other processes such as the spread of cholera will be further discussed in Section 3.3.3.

3.2. Design concepts

3.2.1. Observation

Within the model at the global level, we monitor the following statistics: the proportion of the total number of agents carrying out specific goals (activities), total number of susceptible, exposed, infected and recovered agents both at global level as well as at the individual camp level at each minute of the simulation. We also monitor the rainfall and surface runoff on the environment. These observations will be further elaborated in Section 4. With respect to *Interactions*, the dynamics of the model are driven by the interactions of the agents with their environment. Agents of the same family share resources (e.g. water), they also interact with other agents who are their relatives or friends. Relatives are assigned to agents at the initialization of the model while they select friends randomly at runtime based on spatial proximity to their home (i.e. next door neighbors).

[1] It needs to be noted that data on daily activities within refugee camps is sparse, to say the least. Here we make several assumptions based on Maslow's "Hierarchy of Needs", in essence, first agents must satisfy their physiological needs such as food and water, before seeking out other activities (Maslow, 1943) and human mobility studies more generally (e.g. Gonzalez et al., 2008).

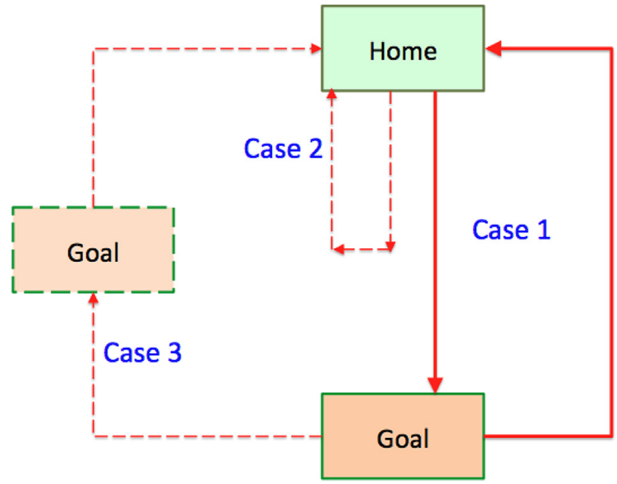


Fig. 3. Agent's movement options between its home and its goal.

3.2.2. Sensing

Agents are assumed to know the nearest facilities, their relatives and friends locations. They also know how to navigate along the road network towards their specific goal. The environment reacts to rainfall and creates surface runoff via the elevation gradient (as will be discussed in Section 3.3.3.2). With respect to *Emergence*, we anticipate the spatial distribution of cholera to be an emergent phenomenon. We class emergence as the large-scale outcome from simple interactions among individual agents (Kelly et al., 2013). Although users of the model can infect a specific number of boreholes to observe the spread of cholera due to the probability of drinking contaminated water, the spatial distribution and spread of cholera from one camp to another emerges due to the simple interactions of individual agents with each other and their environment at the micro level as we will demonstrate in Section 4. *Stochasticity* within the model is seen in several processes. These include the agent selection of certain goals (e.g. going to market) or selecting a friend to visit which are drawn from a normal distribution. The assignment of some properties of the agents (e.g. to be a symptomatic or asymptomatic agent) are assigned randomly at the initialization of the model based on a parameter set by the user (see Section 3.3).

3.3. Details

3.3.1. Initialization

The initialization of the model relies on demographic and spatial data of the study area. Most of the parameter values were calibrated based on relevant literature. Where ranges are used, we apply a normal distribution. In cases where no such data exists, we estimate values by proxy. For example, dehydration rate is estimated by the daily consumption rate of the agent. We assume that agents need to fulfill their water demand daily; hence we calculate the dehydration rate by dividing the minimum daily water use by the number of minutes in a day. All the default values and the parameters are summarized in Table 1.

3.3.2. Inputs

The input spatial dataset were generated from publicly available data sources. The camps information (camp boundaries, houses, facilities, and infrastructure) was processed from UNHCR (2011b) and UNITAR (2012). The elevation dataset was generated using the 90 m Digital Elevation Model (DEM), from the CGIAR Consortium for Spatial Information (2012) GeoPortal.

Table 1
Input parameters and variables.

Parameter	Default values	Reference
Agent		
Initial number of agents	50,000–500,000	User settable
Daily water consumption	4–15 L/day	UNHCR (2011a)/ CARE (2012)
Dehydration rate	0.003 L/min	Authors estimation
Ratio of asymptomatic to symptomatic agent	3:100	King et al. (2008), Harris et al. (2008)
Rate of return to susceptible	0.0001%	Authors estimation
Maximum distance from home to open field latrine	2 km	Authors estimation
Maximum occupancy threshold	100 families per cell	Authors estimation
Road crowed threshold	1000 people per grid cell	Authors estimation
Maximum number of relatives	15 families	Authors estimation
Probability of guest contamination rate	0.5%	Authors estimation
Healthy person body resistance level	1.0	Authors estimation
Health depreciation rate	0.001/min	Nelson et al. (2009)
Clean water source preference probability	70%	Authors estimation
Overall ventilated improved pit latrine coverage	60%	UNHCR (2011a)/ CARE (2012)
Mortality	Up to 50% of infected (untreated). Up to 1% of infected (treated)	Nelson et al. (2009)
Minimum number of Vibrio to cause cholera infection	10,000/ml	Franco et al. (1997) /Nelson et al. (2009)
Cholera infection duration	12–72 h	Nelson et al. (2009)
Infected person fluid loss	1000 ml/h	Nelson et al. (2009)/ Codeço (2001)
Vibrio per gram of stool of infected person	10^7–10^9/ml	Nelson et al. (2009)/ Franco et al. (1997)
Vibrio per gram of stool of uninfected person	10^2–10^5/ml	Codeço (2001)
Minimum goal utility threshold	0.3	Authors estimation
Facilities		
Health facilities capacity	1000 patients/day	
Borehole maximum capacity	2 L/people/day	UNHCR (2011a)/ CARE (2012)
Borehole discharge rate	80% of the maximum borehole capacity	Authors estimation
Rainfall		
Rainfall absorption rate	10 mm/min	Authors estimation
Duration	25 min/day in a rainy day	Authors estimation
Rainfall amount	Daily rainfall (mm) from data	AccuWeather (2013)

Demographic characteristics (e.g. age, sex, number of people per household etc.) for the agents is based on data from and UNHCR (2011b) and CARE (2012).

3.3.3. Submodels

3.3.3.1. Goal selection. It is well known that agent-based decision making is a complex task (e.g. An, 2012; Kennedy, 2012; Filatova et al., 2013). Therefore, rather than taking an overly complicated approach we make it as simple as possible. Agents determine their current goal (activity) based on their personal attributes (e.g. age, sex), and their current need. They also take into consideration the time and distance to the goal when they make their choice. Within the model we make the simplifying assumption that agents who are less than 5 years old stay at home and do not engage in any activities, unless they are infected and need to visit the health facilities.

Agents will select a goal that gives them the highest utility. The next goal selection will be scheduled after the current goal has been executed or aborted. The utility of a goal for an agent is given as follows:

$$U_i = \alpha_i \cdot \beta_i(T) \cdot \gamma_i \tag{1}$$

where U_i is the utility of goal i, α_i is set to a constant value for a specific goal selected from a uniformly distributed random number, β_i is a function of the time period T, which indicates the importance of the time period for a goal, and γ_i is the parameter indicating the importance of a goal. The time period T can be a specific time of a day, day/night cycle, or a specific day(s) in a week depending on the type of a goal. For instance, the selection of 'visit to relatives' goal will have a β value of 1 between 6:00 am to 12:00pm and 0 in other time (i.e. when the agent wants to sleep). The value of a goal G is as follows:

$$Gi = \frac{Ui}{\sum_{i-1}^{n} Ui} \tag{2}$$

And the selected goal will be the one with the maximum G value as follows:

$$A_i = \max_{1 \le i \le n} \left(G_i \right) \tag{3}$$

where A_i is a goal with the maximum utility, G_i is the value of goal i, U_i is the utility of goal i, and $\sum_{i-1}^{n} Ui$ is the sum of all utilities for all of the goals. The A_i value should be greater than the 'Minimum Goal Utility Threshold' to be executed, otherwise the agent stays at home. The assignment of a facility location for the selected goal is based on proximity to the agent. In the model, agents give the highest priority to the nearest facility (i.e. minimum distance) when choosing between two facilities of the same kind. If two or more activities have the same utility, one of these activities will be chosen at random.

3.3.3.1.1. Goal selection – school. Within the Dadaab camp, 51% of children between the ages of 5 and 18 attend school (CARE, 2012). As such, at the initialization of the model this percentage of agents between these ages are classed as students and have the goal of going to school. School is between 8:00 am to 4:00 pm from Monday to Friday.

3.3.3.1.2. Goal selection – religious center. In this model, we only consider one type of religious center. We make our assumption based on both the statistical and spatial data. According to the camp population statistics report from UNHCR (2012), about 95% of the total refugees in the Dadaab camp originated from Somalia who primarily practice Islam. The spatial information also indicates that there are only mosques in the refugee camps as opposed to other religious centers. We make the assumption that agents within our model only visit mosques during the main prayer times: Fajr (5:30 am), Dhuhr (1:00 pm), Asr (4:00 pm), Maghrib (7 pm), Isha (8:00 pm). We also consider Friday as the main communal worship day of the week. In these prayer times or day or both, agents are more likely to visit the mosques rather than carrying out other activities. However, agents who are classed as students only consider visiting the mosques when they are not in school.

3.3.3.1.3. Goal selection – market. Although the main source of food for the camp comes from food aid, refugees also engage in different income generating activities such as petty trading. This is especially the case in refugee camps like Dadaab, which have existed for many years (see Werker, 2007). In the model, the priority of visiting the market depends on age and sex. We assume that most of agents in the age range of 18–46 are more active in such economic activities (Werker, 2007).

3.3.3.1.4. Goal selection – food distribution centers. In Dadaab, food distribution is managed by CARE, an international non governmental organization. According to CARE (2012), the food distribution within the camp is scheduled in order for each family to receive food every 14 days (CARE, 2012). Each refugee family therefore visits the food distribution centers every 14 days. The date of distribution is randomly assigned to each of the agent families at the initialization of the model and each family knows when to visit the food distribution centers. On that date, the agent will give the highest priority for visiting the food distribution center over all other activities. Any one of the agents within the family can visit the food center.

3.3.3.1.5. Goal selection – visiting friends or relatives. Within the model, agents visit friends who live within the same camp (e.g. next-door neighbors). With respect to relatives, these can live in any of the three camps. In both cases the agent selects at random a specific agent's home location and makes the visit its priority and moves towards that agents' home location. If the agent reaches its goal and is dehydrated, the agent can drink water from its hosts' home location.

3.3.3.1.6. Goal selection – health centers. Within the model, agents only visit health centers when they are infected by cholera. Any infected agent will place visiting the health facilities as its highest priority on its list of daily activities. Health centers have a limited capacity with respect to the to treatment patients (a default parameter).

3.3.3.1.7. Goal selection – water points. In this model, two types of water sources are considered. The first one is from boreholes or tanks, which are mainly delivered and administered by humanitarian organizations. These water sources are considered as clean unless pollution is introduced exogenously. The second source of water is from rainfall. Agents can utilize surface water that might be accumulated in ditches or holes after it rains. Water from this source can easily be contaminated by surface runoff, mainly due to feces. In this case, water pollution takes place endogenously through surface runoff and feces accumulation.

Within the model, water is collected by any member of the family and is equally shared with all family members. The maximum daily consumption of each agent is 15 L per day (CARE, 2012). This amount includes all possible uses of water: drinking, cooking and cleaning. There is a notion of dehydration in the model: at each time step, agents check both their body water level and their family water levels to make decision whether to fetch water or not. Agents fetch water from the nearest water sources and utilize the water. Agents can fetch up to 25 L in a single visit depending on the availability of water from the sources. If the source is dried up or very crowded, agents will visit other nearby water points to achieve their water goal.

3.3.3.1.8. Goal selection – latrine. We consider two types of sanitation facilities in the model: ventilated improved pit latrine (VIPL) and open field latrine (OFL). The VIPL is viewed as safe as they can easily contain waste. The number of VIPL in the model is set as a parameter and the user can change the value. Agents may or may not have access to VIPL. If they do, they utilize them. However, if they do not have access to one, an agent will utilize the nearest open space as a latrine (i.e. OFL). Their disposal (i.e. waste) will stay in the environment and can be washed away by rain water runoff and can cause the contamination of rainfall water if used for water consumption. In the model, infected agents will visit any latrine more frequently than other agents.

3.3.3.2. Hydrology. Within our model, we use rain as a proxy for climatic events, as previous research has shown that there are strong correlations between seasons and outbreaks of cholera (e.g. Reiner et al., 2012). Secondly, as noted, above water is one of the main methods for cholera transmission (e.g. Codeço, 2001). In this model, we use rainfall both as source of drinking water for the agents as well as a carrier of cholera bacteria (e.g. via feces). We utilize a DEM as shown in Fig. 4 to model the flow of rainfall over the ground. We apply a simple hydrological model that only considers the elevation gradient (slope) to model surface runoff. Rainfall flows downhill according to the slope. As the water flows from uphill to downhill, it carries pollutants (e.g. the cholera bacteria). The concentration of pollutants in the water depends on the amount of pollutant per volume of water in the field unit (i.e. cell). As the model has been purposely kept simple, we have not considered issues such as subsurface flows, soil moisture, or evaporation such as in the work of Bithell and Brasington (2009) or Beven and Freer (2001). While our simplifying assumptions might impact the spread of water and pooling, a more complex hydrological model was considered beyond the scope of this study.

The dynamics of the surface runoff is modeled using a cellular automata technique. As rain falls over the entire study area, each cell receives an equal amount of rainfall. At each time step, each cell will check if it has water to flow to its Moore neighbors. If the cell has water and the neighboring cell is a sink (i.e. at a lower elevation), it will give the water to that cell until it fills the sink depending on the elevation and water gradient and *vice a versa*. Water flow is treated as follows:

$$V_t^c = \begin{cases} V_{t-1}^c + \sum_{i=1}^{n} \partial^i V_t^i - \zeta + R_t^c, & \text{if } h_c < h_i \\ V_{t-1}^c - W_t^c - \zeta + R_t^c, & \text{if } h_c > h_i \\ V_{t-1}^c - \zeta + R_t^c, & \text{if } h_c = h_i \end{cases} \tag{4}$$

where V_t^c is the volume of water of central cell at time t, V_{t-1}^c is the volume of water at previous time step, V_t^i is the volume of water of the neighboring cell at time step, ∂_t^i is a parameter indicating the proportion for water flow from a neighboring cell, W_t^c is the outflow volume of water from the central cell. The model contains a consistency condition for water flow, by matching the outflow W_t^c to the total volume of water that is available in the central cell. ζ is the volume of water lost through absorption (which is a constant for all cells), R_t^c is the volume of rain at time t for the central cell, h_c and h_i indicates the height of central cell and neighboring cell respectively, n indicates the number of neighboring cells.

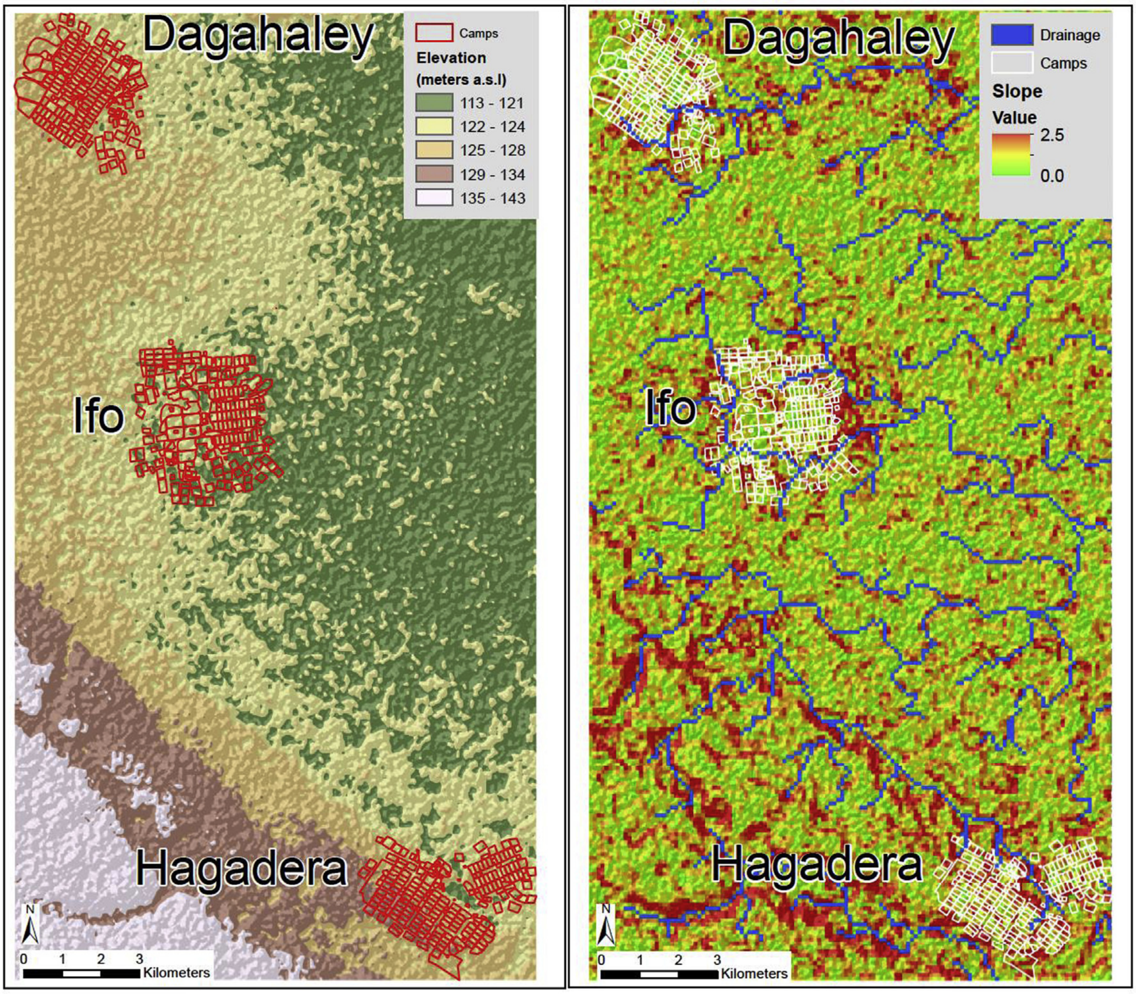
The height h includes both the elevation and the depth of the water level as:

$$h = \text{elev} + \frac{\text{Volume}}{\text{Area}} \tag{5}$$

Water that accumulates in the sinks can be considered as puddles or sources for drinking. As rainfall flows from cell to cell, the total amount of pollutant in the water changes accordingly. The flow of pollutant also depends on the volume of water, thus the total amount of pollutant is given as:

$$P_t^c = P_{t-1}^c + \sum_{i=1}^{n} \vartheta^i P_t^i - Q_t^c \tag{6}$$

where P_t^c is the total amount of the pollutant of the central cell at time t, P_{t-1}^c is the amount of the pollutant at the previous time step, P_t^i is the amount of the pollutant of the neighboring cell at time t, ϑ is a parameter indicating the proportion for water flow from a neighboring cell, and Q_t^c the pollutant loss through outflow. With respect to the surface boundary conditions, within the model we assume rainfall is evenly distributed throughout the study area and when water reaches the edges of the domain it does not accumulate but rather flows out and carries the pollutants with it. In addition, we assume that at the start of the simulation, the study area does not contain any bacteria in the soil (this is discussed further in Section 4.2).



A B

Fig. 4. Digital elevation data used within the model (A) and the resulting slope differentials (B) with the refugee camps superimposed on top of them.

3.3.3.3. *Cholera SEIR model.* Cholera is caused by the *V. cholerae* bacteria, which can survive in aquatic reservoirs or the host's intestine. Our intention is to explicitly represent the interaction between the host (i.e. human) and the environment (i.e. aquatic reserve) by utilizing Susceptible-Exposed-Infected-Recovered (SEIR) model to capture the time between ingestion of contaminated water and showing the symptom (i.e. the incorporation of exposed), which is different from previous models of cholera which utilized the SIR model (e.g. Tuite et al., 2011; Augustijn-Beckers et al., 2011).

All the refugee agents are considered as susceptible hosts as shown in Fig. 5. The infectious dose of *V. cholerae* in humans varies greatly depending on the bacterial strain and the host. In many cases, a bacterial cell concentration of 10^3/ml of water is necessary to infect the host (Nelson et al., 2009). We assume that a susceptible agent who ingests contaminated water with a bacterial cell concentration of 10^3/ml or above will become exposed to the cholera disease. An exposed agent stays as exposed for 12–17 h before showing any symptom (Nelson et al., 2009 [2]). This lag period depends on the age, and body resistance of the agent. Infants show symptoms more quickly than adults (Harris et al., 2008). After the lag period, exposed agent will pass into the infection phase.

We distinguish two types of infectious agents: symptomatic and asymptomatic. Symptomatic agents are those who show symptoms of cholera and can die from the infection. Symptomatic infected agents spread 10^9/ml of *V. cholerae* through excretion of feces to the environment and the bacteria can survive in the environment for long period of time (Franco et al., 1997). Asymptomatic agents can shed 10^2–10^5/ml *V. cholerae* per stool to the environment without showing any sign of symptom (Franco et al., 1997). In our model, asymptomatic agents immediately pass to the recovery stage while symptomatic agents stay in the infection phases until they get treatment and recover. If they do not get treatment, they will die. A recovered agent will stay as recovered for some time (approximately two years) before becoming susceptible again (Nelson et al., 2009). A susceptible or recovered agent may also spread small amounts of *V. cholerae* through excretion of feces (Franco et al., 1997). We also assume within the model that if *V. cholerae* is excreted into the environment, it can stay alive for the simulation period by transforming into a Viable But Non Culturable (VBNC) state until it gets into the host intestine through ingestion of contaminated water. *V. cholerae* cells in the VBNC state are living cells and can continue survive in the environment for more than 100 days (Li et al., 2014; Chaiyanan et al., 2001; Colwell, 2000; Wai et al., 1999).

[2] However, the literature notes that infection rates can vary after ingestion and this is an area of debate (see Hartley et al., 2006).

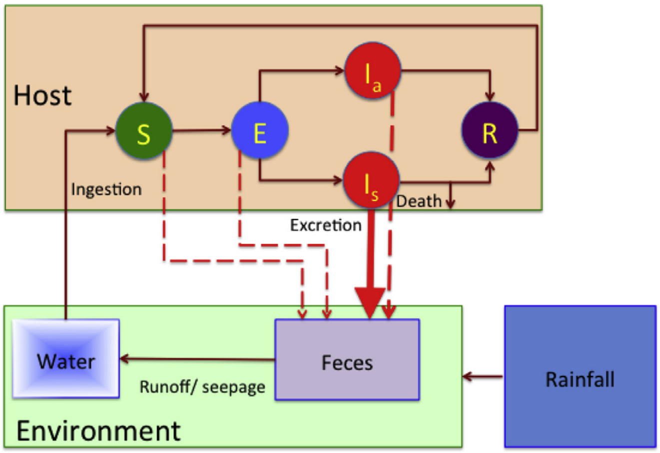


Fig. 5. Cholera transmission through the interaction of host and the environment. The progress of cholera transmission is represented as SEIR model. S = susceptible, E = Exposed, Ia = Infected (asymptomatic), Is = Infected (symptomatic), R = Recovered.

3.3.4. Model outputs

The main outputs from the model include the number of people who are susceptible, exposed, infected and recovered per iteration of the model, along with the spatial location of the individuals. Through such outputs we can trace the spread of cholera throughout the refugee camps.

4. Results

Before presenting the results of the model, it is important to discuss verification. We refer to verification as the process of checking that the implemented model matches its design (North and Macal, 2007). Verification of the model was performed by conducting code walkthroughs, profiling and parameter testing to ensure the model was working as intended. These tests insured that we made no logical errors in the translation of the model into code, and that there were no programming errors. After carrying out these tests, we feel confident that the model behaves as it is intended and matches its design.

In this section, we present results from two experiments that are focusing on the spread of cholera caused by two potential sources of water contamination within the refugee camp complex. In the first experiment (Section 4.1), we contaminate one borehole within the Ifo camp with cholera, which could be associated with say a leak from a VIPL. In addition, we explore how restricting movement impacts on the spread of the cholera. While in the second experiment (Section 4.2), we introduce rain into the model and allow agents to drink from both surface water and water from boreholes to explore how rainfall impacts on the spread of cholera. Both of these scenarios act as a way of testing the inner validity of our model but also demonstrate how the model could be used to simulate a cholera epidemic or to explore endemic cholera. What is presented in the remainder of this section is the average of 50 model runs with different numbers of agents which amounts to 450 runs. The default parameters are presented in Table 1.

4.1. Scenario one — contamination of a single borehole

Here we explore how a contaminated water source in the Ifo camp can trigger a cholera outbreak. Fig. 6 shows the dynamics of susceptible, exposed, infected, and recovered refugees within the Dadaab camps with different population size (which tests how sensitive the model is to population densities) and with two different movement rules (e.g. movement between camps (Fig. 6A)

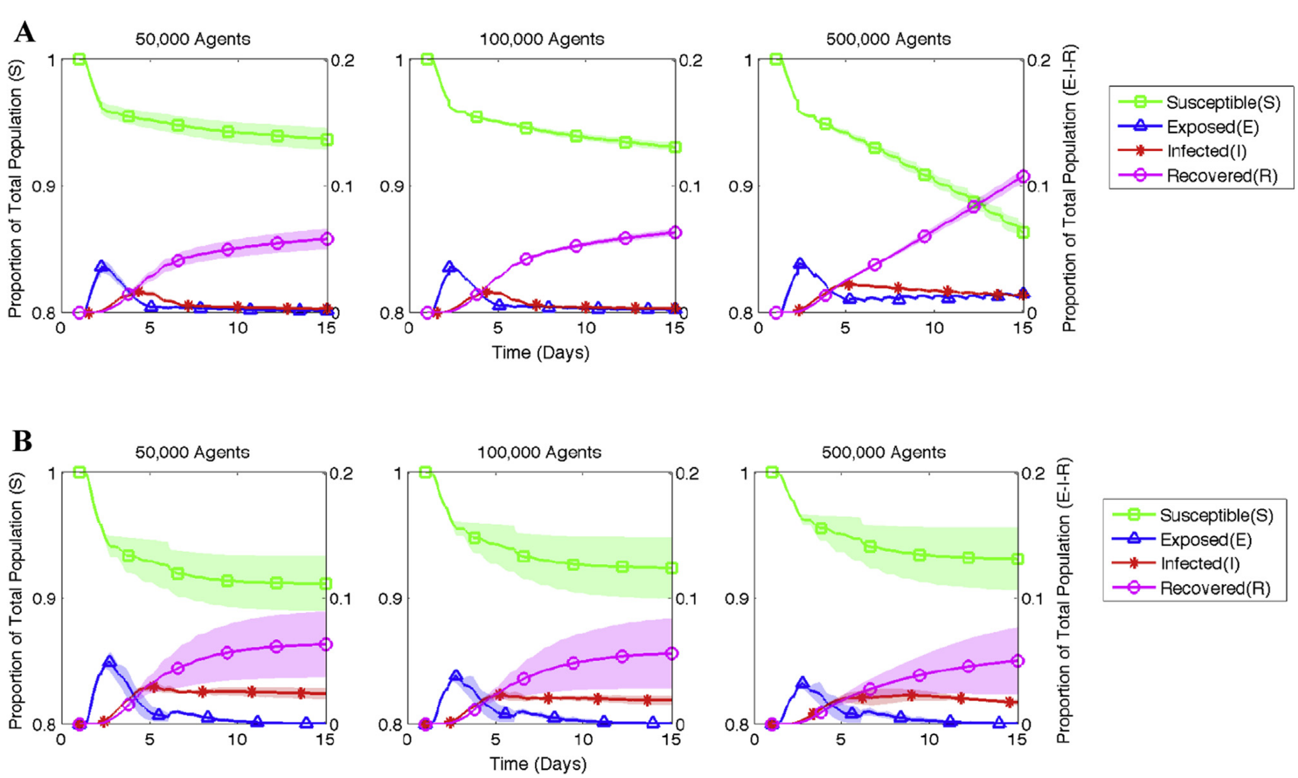


Fig. 6. Proportion of the population susceptible, exposed, infected and recovered with different initial populations. Solid lines represent the average and shaded areas represent the standard deviation of model runs around the mean. A: with movement, B: no movement between camps.

and no movement between camps (Fig. 6B). In all cases, the cholera outbreak follows a traditional epidemiological curve. Those agents who had access to and who ingested contaminated water, rapidly passed from susceptible to the exposed stage. This exposure resulted in a spike in the cholera epidemic in the first four days and gradually died down by about seventh day, by which time approximately 2% of the total population in the entire camp were infected with cholera.

The model results also indicate that the cholera outbreak can be influenced by both accessibility (in terms of movement between camps) and the number of refugees within the camp. As shown Fig. 6A, by increasing the number of refugees from 50,000 to 500,000, the proportion of infected refugees grows especially when agents continue to move between the camps. While the number of water sources and the fraction of people who visit their relatives remain constant, this is not the case for the number of refugees who go and get water. Hence, the number of refugees who have access to the infected borehole increases as the number of refugees increases which therefore increases the proportion of agents infected as they visit their relatives or friends. In addition, such movement allows the infection to persist for a longer period of time, even after the initial outbreak. This is mainly because by increasing the number of refugee agents in the system increases the probability of a refugee from either of the other two camps to prioritize a goal to visit friends or relatives who have access to the contaminated water source as the simulation progresses. This is not seen when movement is restricted and all population sizes result in the same proportion of infected agents as shown in Fig. 6B. When we explore the infection curve of each camp as shown in Fig. 7A and B, a similar trend can be seen. The oscillations seen within Fig. 7A are the result of the refugees' activities' which are predominately day time activities unless infected and thus seeking medical attention (see Section 3.3.3.1). Therefore, the refugees have a greater chance of being exposed to cholera during the day, but as it takes time to be infected this creates a lag (oscillations). This pattern is made more noticeable when the proportion of infections is disaggregated by camp.

When movement is restricted however, between the camps at the onset of the cholera outbreak, no infections occur outside the Ifo camp as shown in Fig. 7B. However, there is more variation between individual runs as can be seen in Figs. 6B and 7B. This can be explained by agents activities being limited to their specific camp and not being able to travel between camps, which takes more time; therefore the agents are able to carry out more activities and as such have a greater potential to becoming infected as they visit friends or family in the infected area (as discussed in Section 3.3.3.1).

In Fig. 8, we show a typical run of the model where the number of infected cholera cases by location changes over time. The spatial pattern of cholera is much more localized around the contaminated water source within the Ifo camp. As time progresses, the spread of the disease grows radially from the contaminated water source and starts to affect agents who are living far from the source. Looking at spatial spread of the infection also indicates that the restriction of agents movement affects the pattern and extent of the spread of cholera. As shown in Fig. 8B, cholera infection is confined to the Ifo camp when movement was restricted at the start of the outbreak. However, when refugee agents were allowed to move between camps, cholera also spread to the Dagahaley and Hagadera camps as shown in Fig. 8A.

4.2. Scenario two – contamination through runoff

In this scenario, we explore the notion that cholera is endemic within the refugee camps and can outbreak at any time especially when it rains. Therefore in this scenario, we incorporated actual daily rainfall data (in this case 2011) into the model. We randomly choose a time of the day when it started raining and allow the rain to continue for a maximum of 4 h depending on the amount of the rain (because this area is know for sudden downpours compared to

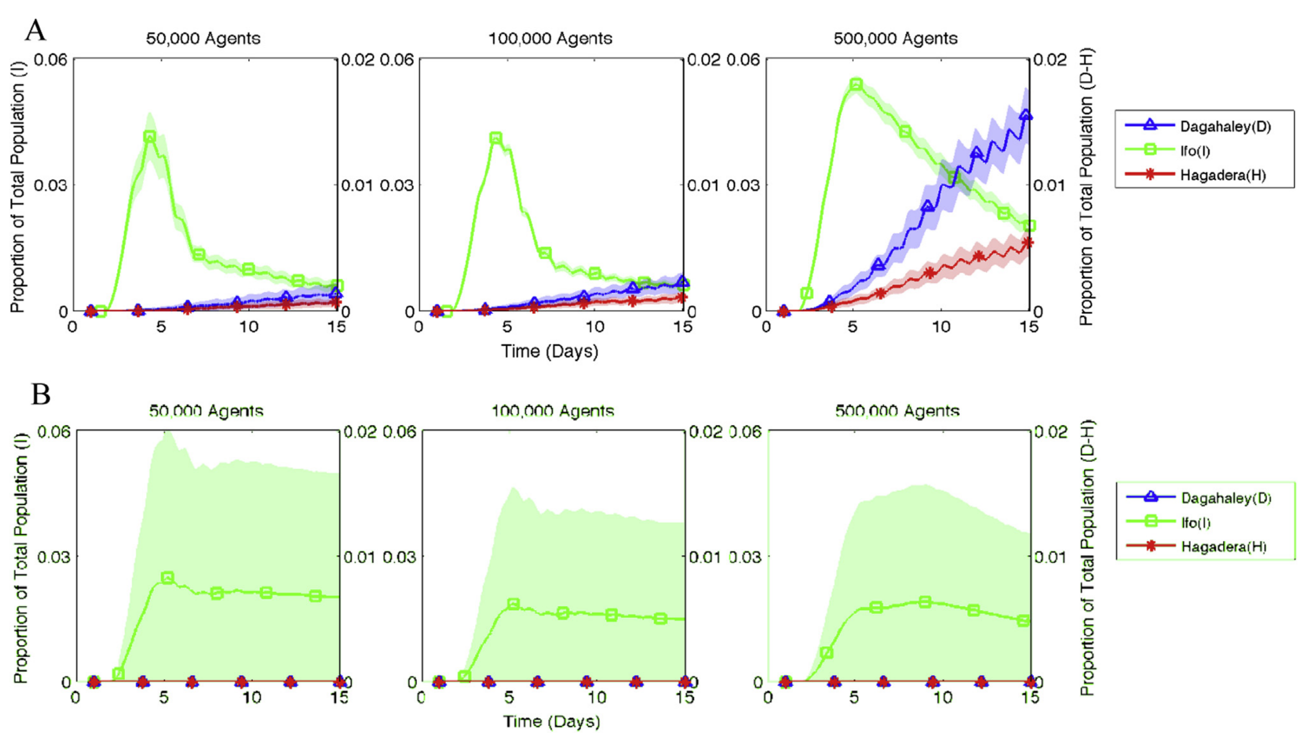


Fig. 7. Proportion of the population infected with cholera split between the three camps. Solid lines represent the average and shaded areas represent the standard deviation of model runs around the mean. A: with movement, B: no movement between the camps.

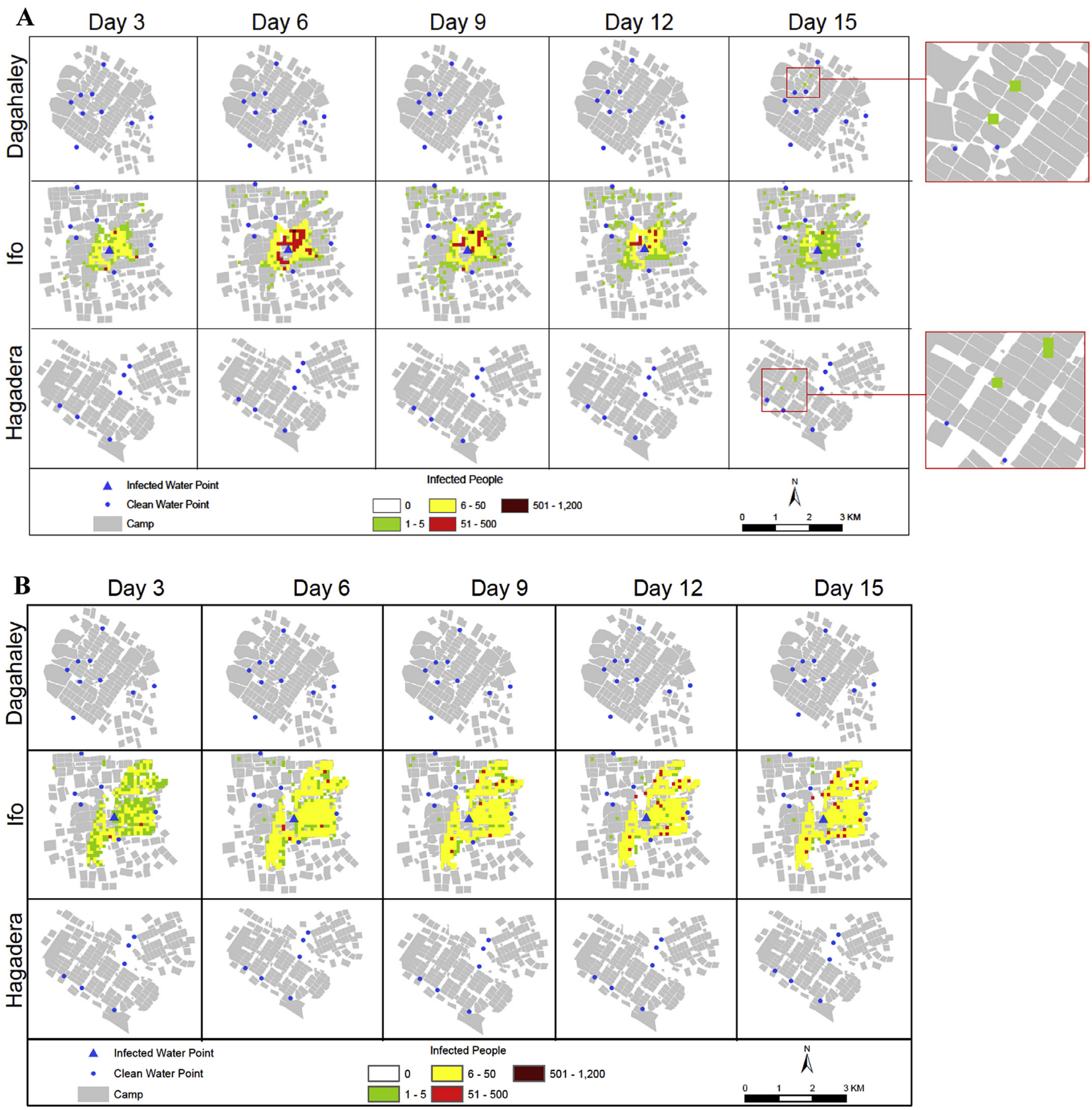


Fig. 8. Number of infected people by camp over time (days) during a simulation run with 500,000 agents, A: with movement, B: no movement between camps.

a constant drizzle). We also assume that the cholera bacteria exists in the feces and that it survives in the environment after defection unless it is either ingested by the refugee agent or carried away through runoff and leaves the area (as discussed in Section 3.3.3.3). Furthermore, agents utilize water from two sources, either from 1) boreholes or tanks 2) rainfall, which is mainly accumulated via surface runoff (see Section 3.3.3.2). In the previous scenario, agents only drank from boreholes or tanks, here we allow agents to have equal preference for water from any source. At the start of the scenario we have a pristine environment, in the sense that there is no cholera bacteria within the soil. This assumption is based on the fact that we do not have any information pertaining to the amount of cholera bacteria already in the environment. However as shown in Table 1 we know that uninfected people can carry a small amount of the bacteria in their body and excrete this in their stools.

As can be seen in Fig. 9, the results show a continuous occurrence of cholera infections in the camp over the one-year simulation period. As more agents become infected with cholera, they contaminate the environment as they are more likely to use OFLs. With more and more agents using the OFLs, the amount of cholera bacteria in the environment increases and is carried by runoff and thus exposes more refugee agents, thus resulting in more cholera cases. This can be easily seen in Fig. 9A, in which the magnitude of cholera spread increases as the number of agent in the system

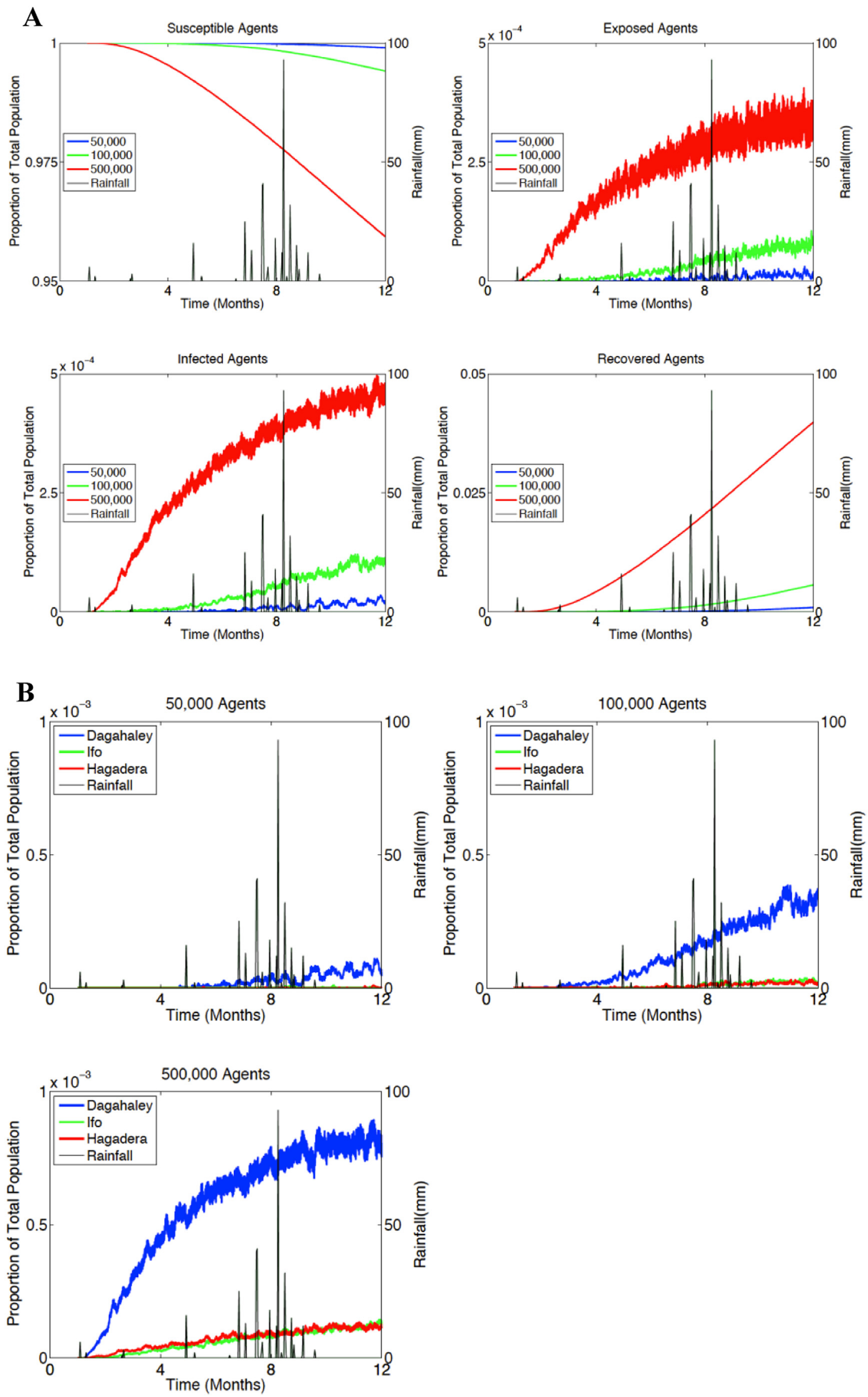


Fig. 9. Cholera dynamics when rainfall is introduced. A: Proportion of the population susceptible, exposed, infected and recovered agents. B: Infections in each camp during the simulation runs. Black lines represent rainfall amounts (mm).

increases from 50,000 to 500,000, which is intuitive: as more agents defecate the more bacteria builds up in the environment. However, it needs to be noted that despite starting with a pristine environment, the amount of bacteria builds up over time due to the agents behaviors and with the first rains it infects a population which is mainly susceptible to the bacteria. However, over time as people become immune the bacteria, the rainfall has less of an impact.

The flow of water with respect to the impact of the spread of cholera is illustrated in Figs. 9B and 10. Runoff along the elevation gradient (slope) affects the concentration of cholera bacteria in the environment (as discussed in Section 3.3.3.2) and aggravates the outbreak cholera in specific locations as bacteria is washed from the higher to the lower gradients or pools in flatter areas (see Fig. 4 for elevation and slope data) and thus makes water in the lower elevations or in flatter areas more dangerous to drink. Such a phenomena creates a situation in which camps that are located in the lower elevation or are flatter (with respect to differences in slope) are more liable to cholera outbreaks than those in the higher elevations or steeper slopes. This can be seen in Fig. 9B, specifically the Dagahaley camp which is the most affected with respect cholera outbreaks. This can be explained as Dagahaley is located on a terrain that is less steep and the range of elevation is the least compared to the other camps. Such a finding is also supported from reports of cholera outbreaks from the camps during 2011 (see UNHCR, 2011a) and gives some qualitative validation to our model.

5. Discussion and conclusions

Cholera is a constant threat in many parts of Africa and Asia. It is estimated to kill between 100,000 and 150,000 people per year. Within this paper, we have developed a spatially explicit agent-based model to explore the spread of cholera within a refugee camp, and applied our model to the Dadaab refugee camp located in Kenya as an example test case. We model the spread of cholera by explicitly representing the interaction between humans (host) and their environment, and the spread of the epidemic using a Susceptible-Exposed-Infected-Recovered (SEIR) model. By purposely modeling mobile and goal oriented individuals engaging in daily activities all of whom are susceptible to the disease, agents can become infected and spread cholera bacteria through excretion of feces to the environment and allowing the disease to spread throughout the system.

Through our scenarios, we have shown how cholera can spread either through the contamination of water or through runoff via rainfall. These scenarios demonstrate how our model can be used to simulate a new infection of cholera or model the endemic nature of cholera, if it already exists within the system. In scenario one (Section 4.1), results show that the spread of cholera grows radially from contaminated water source and that by restricting agents movements during an outbreak, its intensity can be reduced. In scenario two (Section 4.2), we modeled the spread of the cholera bacteria using a simple runoff model linked with rainfall and found that we have outbreaks of cholera, which are in qualitative agreement to what is seen within the camp, specifically within the Dagahely camp (UNHCR, 2011a). This is a result of the rainfall carrying the cholera bacteria to lower elevations or pooling in flatter areas.

This modeling effort highlights the potential of agent-based modeling to explore the spread of cholera in a humanitarian context. It demonstrates that space matters in the modeling of infectious diseases, and how shared water resources can propagate the spread of diseases, which is supported by other studies (e.g. Nunn et al., 2014). Moreover, this style of modeling provides an opportunity to test ideas and hypothesis, which are difficult to do in reality. While this is a prototype model, once further developed, one could explore how different treatment regimes impact on the spread of cholera or ask 'what if' questions. For example, should areas of high exposure be vaccinated first?, and how would this action reduce the number of infected individuals? However, before

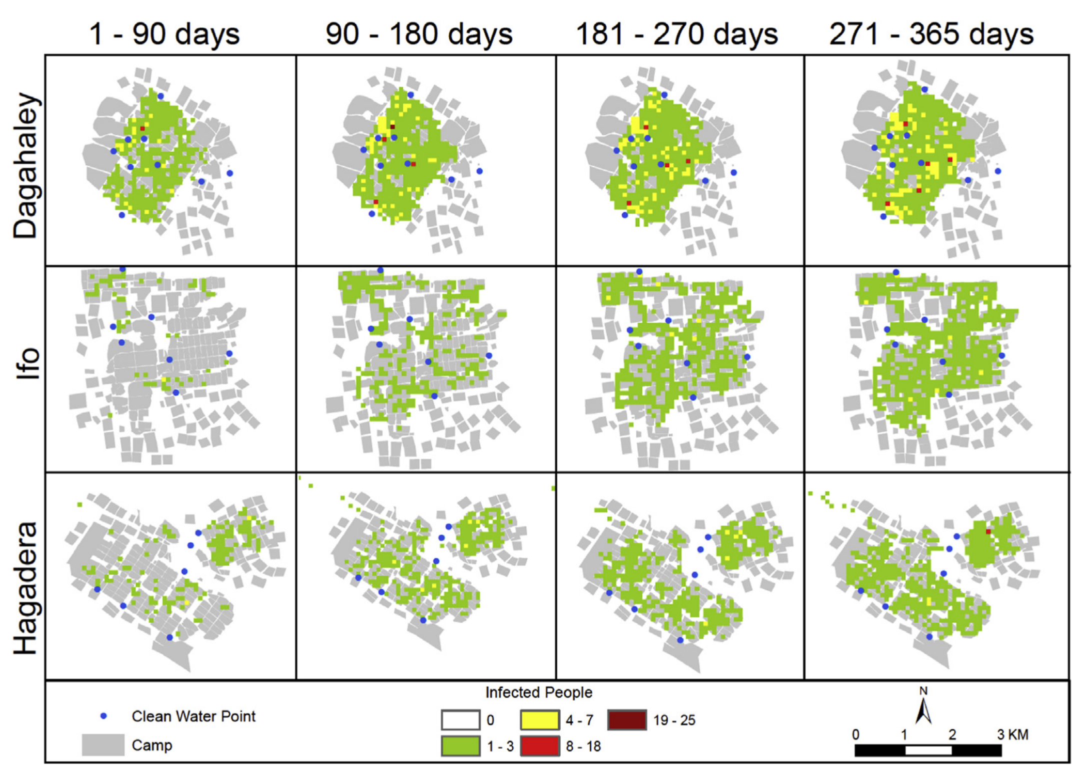


Fig. 10. Spatial spread of cholera over the course of a year during a simulation run with 500,000 agents.

moving in this direction it would also be worth exploring in greater detail the agents activity regimes and movements. For simplicity reasons, we have only represented in this work a subset of the dynamics one would see in a refugee camp or even in a cityscape. However, a more involved representation of movement dynamics and activity routines, such as in the work of Torrens (2012), could be of particular value in expanding and explaining the transmission of the disease.

One challenge we had with validating the model is access to longitudinal data with respect to cholera epidemics within the Dadaab camp. In developing countries this is often the case, data lags behind the actual outbreaks of cholera or in many situations data does not exist. Even when data does exist, as in our case, it is at a very coarse level. Having access to epidemiological data is considered important as detecting the rate in the number of cases at the start of a cholera outbreak provides valuable information with respect to the spread of cholera (Mukandavire et al., 2013). While one can model what triggers the cholera outbreak, such as in the ones presented in this paper, knowing more about the extent of cholera bacteria such as the amount of cholera already in the system, be it in the soil or in a given number of hosts, would allow us to explore further the seasonal outbreaks of the disease. Another area of research could be to explore how news reports or social media can be used to predict trends in future outbreaks rather than having to rely on traditional data sources (e.g. Chunara et al., 2012) and then this could be used to validate our model. Combining new sources of information along with crowdsourcing efforts to map refugee camps and further model development could allow the model presented in this paper to act as an early warning system for the outbreak of cholera for humanitarian response.

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