Integrating Spatial Intelligence for risk perception in an Agent Based Disease Model

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Abstract

An increasing number of spatial agent based models (ABMs) use artificial intelligence to enhance agents' decisions. There is a difference between ABMs with pure social intelligence based on information exchange among agents and ABMs with integrated spatial intelligence. Spatial intelligence refers to the fact that agents sense their environment, perform a judgement on the condition of this environment, and change their behaviour based on this judgement. When spatial intelligence is used in ABMs, it often facilitates navigation (human or animal) or adaptation to land cover change. Less implementations are available for assessing risky situation engaging agents' risk perception. In this paper, we present a model that uses a combination of spatial and social intelligence to simulate disease diffusion. Agents evaluate changes in floating plastic debris in a river combined with personal information and media attention on cholera to decide which water source to use. Cognition of agents with respect to perceiving risk and acting upon it is implemented via two Bayesian Networks. Modelling results are compared with data collected during a Massive Open Online Course. Results of the ABM show a strong decline of the number of disease cases after implementation of artificial intelligence. Results from the survey confirm the fact that people judge quality of water visually, but also show the strong influence of communication on risk perception.

Keywords: spatial intelligence, disease modelling, agent-based, Bayesian networks.

1. Introduction

Spatial intelligence is one of the elements of the theory of multiple Intelligences developed by Gardner (2006). In agent-based models, spatial intelligence is often applied for navigation (human or animal) or adaptation to land cover change (Kocabas and Dragicevic, 2013). Fewer examples exist in which spatial intelligence is associated with spatial risk perception. How does the spatial environment, and especially changes in this environment, influence individual risk perception? How can artificial intelligence algorithms assist in creating spatially and socially intelligent agents operating in risky environments?

Risk perception is often the result of a combination of signals that a person receives. It may result from information received via (social) media, direct communication or observations made in the spatial environment (change detection). The judgement of all of these signals may differ per individual based on four factors including the type of risk, the context in which the risk is perceived, the personality of the person and the social context (Wachinger and Renn, 2010). Psychology approaches this subject using Protection Motivation Theory (PMT), which is often applied in the health domain (Maddux and Rogers 1983; Xiao et al. 2014). PMT assumes that a person facing a risky situation goes through a two-stage cognitive process: risk appraisal followed by a coping appraisal. The former is about checking risk and evaluating if risk perception is high enough to take action. The latter stage concerns possible options and taking an action.

Risk perception can greatly impact the spread of diseases (Kitchovitch and Lio, 2012). When individuals are aware of risk, they may change their behaviour to prevent infection. Often the risk awareness is modelled at two levels: global level and location or personal level (Kitchovitch and Lio, 2012). In these models, no split is made between social and spatial elements. In this research, we focus explicitly on the spatial risk perception.

Risk perception is complex and therefor can best be implemented using Artificial Intelligence. In this research, we will use an existing agent-based cholera model to include spatial risk perception using Bayesian Networks. As little data is available on spatial risk perception, we will collect behavioural data using a Massive Open Online Course (MOOC).

Objectives of this paper are twofold:

- To examine the effect of spatial and social risk perception on disease spread
- Compare the risk awareness of agents with data collected on risk perception of MOOC participants.

2. Methods

2.1. Model

For this study we used the cholera model for Kumasi Ghana developed by Augustijn et al. (Augustijn et al., 2016). Figure 1 illustrates the processes included in this Cholera ABM model that every agents pass through during the simulation. As it is impossible to visually detect the presence of cholera bacteria in water, we assume that the safety of drinking water is assessed via the level of visual pollution at water collection points. The fact that individuals rely on personal observations when assessing the quality of drinking water is supported by literature (Crampton and Ragusa, 2016).

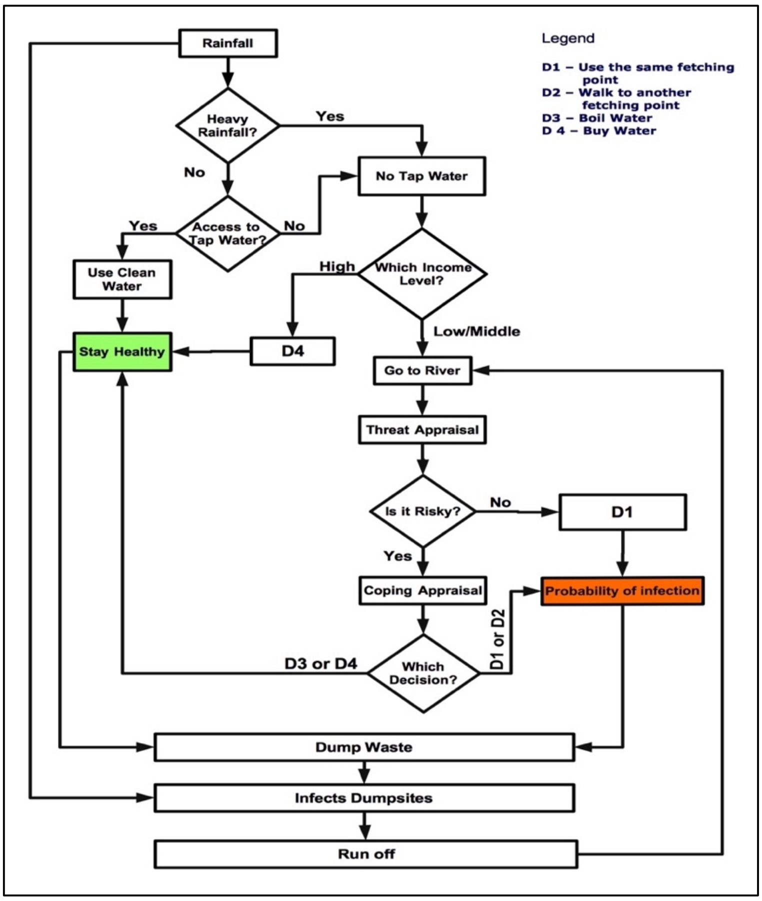

Figure 1: Implementation of Cholera Processes including PMT

We model floating plastic debris in river water spread by heavy rainfall and use the perception of pollution as an indicator for the safety of the drinking water. When dumpsites are present at the riverbanks it is likely that some dumped materials will end up in the river. We refer to this as basic visual pollution (VP1) this can also be interpreted as the rate at which garbage enters the river. VP1 is calculated for every water collection point once a day based on the number of open refuse dumpsites that are located within a distance of 200 meters from the river. Thus, the basic visual pollution is modelled as:

$$f(VP1) = \sum_{i=1}^{N} \frac{x\,g}{d} \qquad \textbf{Equation 1}$$

where N is the number of dumpsites around the river water collection points; x is the number of households who use the dumpsite; g is the amount of garbage produced by each household; and d is the distance from the dumpsites to the water point ($1 \text{ m} \leq d \leq 200 \text{ m}$).

We assume that during dry days the garbage in the river will remain relatively static (limited amount will be transported). The implementation of VP1 leads to variation in visual pollution in space (water looks visually clean around the springs and more polluted in downstream areas) and in time (water becomes more polluted during and after heavy rainfall). We combine the risk perception via spatial cognition with other factors that induce risk. This includes media, memory and personal communication.

2.2. Cognition

Cognition was implemented using a twostep Bayesian network (BN) to imitate the two PMT steps. One BN is for risk appraisal, i.e. assessing risk perception of individual agents based on a combination of signals (environmental, social and personal communication). The second BN is for coping appraisal to select the alternative water sources that used by the agents. The second BN can lead to four different alternative actions: use the river water, try to find a cleaner location to collect river water, use the river water after boiling, buy bottled water.

2.3. Data collection

Since little is known about spatial risk detection especially in developing countries, we collected data during the MOOC GeoHealth (2016) that embraced 3500 participants from 92 countries (54% of them were from Africa including Ghana). Participants were divided into four groups of equal size and were shown different pictures of rivers. These pictures differ in colour of river water and level of floating debris (only on banks – in banks and in water). All participants answered the same questions, in which we tested two elements:

- their trust in the quality of the water based on visual perception only
- their trust in the quality of the water based on visual perception in combination with other types of information (media, communication).

2.4. Experiments

We conducted experiments with VP1 (visual pollution around dumpsites Figure 2) and compare the impact of various factors on the dynamics of risk perception in the agent population with the outcome of the MOOC survey

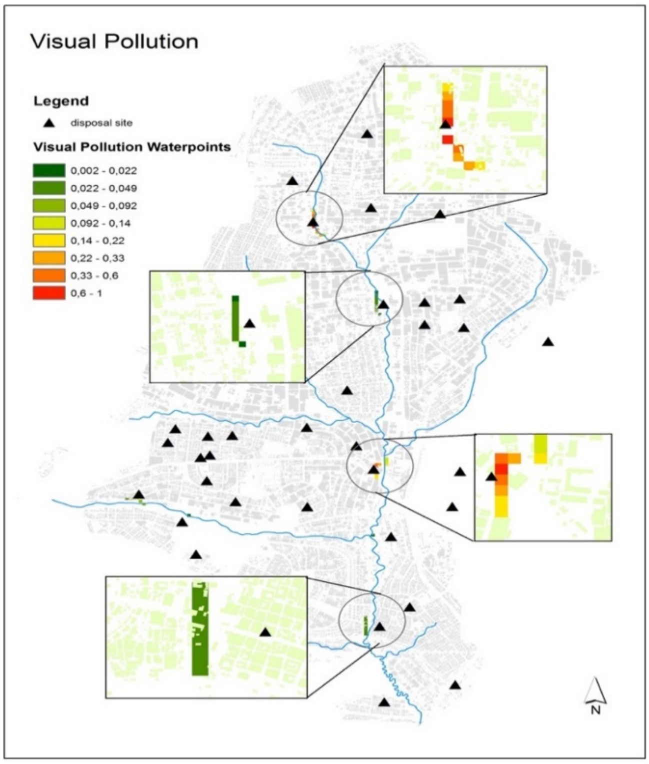

Figure 2 Simulated levels of visual pollution (VP) around open dumpsites. Higher levels of VP are observed for dumpsites closer to the river.

3. Initial Results

The data collected during the MOOC GeoHealth indicates that people indeed judge the quality of drinking water by visual appearance. Where the cleanest water scores 67% on willingness to drink the water, the most visually polluted water only scores 20% (Table 1). We also observed that the impact of media and neighbour contacts as willingness to drink the water drops to 16 and 18%.

When comparing the results of the African participant group with the total MOOC participant group we see that more people (78%) have willingness to drink the cleanest water, and also more people (40%) use the most polluted water (Table 1).

Table 1: The percentage of individuals/agents that use the water, in which ABB is a picture showing clean water, BBA is a picture with brown water but no plastic debris, AAB has plastic debris on the river banks, and ABA has plastic floating in the water

Perceiving Risk elements	MOOC (all participants)				MOOC (Africa Participants)				Cholera ABM
	ABB (%)	BBA (%)	AAB (%)	ABA (%)	ABB (%)	BBA (%)	AAB (%)	ABA (%)	(%)
Visual Pollution only	67	55	24	20	78	54	33	40	92
Visual pollution and communication with neighbours	16	30	22	10	17	46	50	13	52
Visual pollution, communication with neighbours and media	18	23	20	6	11	31	33	7	22

When we compare these values with the agents that used BN1 (perceived risk) in the simulation model the modelling experiments show values that are considerably higher (92%, 52% and 22%) compared to the MOOC values. This is not surprising as MOOC participants are normally highly educated and are more risk aware.

The communication with neighbours has an impact on individuals risk perception in the model which is in line with African MOOC participants. The combination of all three types of information has the stronger impact on risk perception in the model as well as in the MOOC, 22% of the agents in the cholera model use the water.

After perceiving risk and rejecting to drink the water a choice has to be made on alternative water sources (coping appraisal captured in BN2). MOOC participants were only given the choice between two alternatives (e.g. use the water or walk to another location) whereas the agents in the simulation could choose from all coping options.

The results of the MOOC indicate that a high percentage is willing to walk to an alternative location or boil the water (Table 2). The results for African participants are comparable to total participant results.

In the simulation after using BN2, 27% of the agents walked to a different location to fetch water, 69% boiled the water and the remaining agents used the water as is or bought bottled water.

Table 2: Willingness of MOOC participants to walk to an alternative location or boil the water.

Individuals/Agents Decision	MOOC (all participants)				MOOC (Africa Participants)			
	ABB (%)	BBA (%)	AAB (%)	ABA (%)	ABB (%)	BBA (%)	AAB (%)	ABA (%)
Walking to another location/water source	71	85	90	94	72	69	67	93

Using current water after boiling it	84	80	61	59	89	69	83	67

When implementing the two BNs, we see a drop in the total number of disease cases to a level of approximately 10% of the original numbers. This confirms the findings of Kitchovitch and Lio (2012) which implies the role of risk perception in the dynamics of disease transmissions. The number of disease cases for only BN1 at the risk appraisal stage are comparable to the results of using both networks. However, we see a clear trend towards using safer water sources.

The spatial patterns of disease cases show 15 – 20 % of the total cases in areas which are close to springs (upstream). This implies that although agents were looking for visually clean water they still get infected.

Risk appraisal based on spatial intelligence is not easy to measure. Limited data are available about the way the spatial environment impacts human decision making. Most sources discussing risk perception will evaluate how risk perception varies in space but not which role the environment itself plays in the process of feeling scared. Implementation of spatial intelligence in agent-based models is relative straightforward. Yet, finding suitable data to validate the processes remains a challenge.

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