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Growing Food Safety from the Bottom Up: An Agent-Based Model of Food Safety Inspections

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Abstract

The overall burden of foodborne illness is unknown, in part because of under-reporting and limited surveillance. Although the morbidity associated with foodborne illness is lower than ever, public risk perception and an increasingly complex food supply chain contribute to uncertainty in the food system. This paper presents an agent-based model of a simple food safety system involving consumers, inspectors and stores, and investigates the effect of three different inspection scenarios incorporating access to information. The increasing complexity of the food supply chain and agent-based modeling as an appropriate method for this line of investigation from a policy perspective are discussed.

Keywords:

Agent-Based Modeling, Search, Food Safety, Inspection, Policy



Introduction

- 1.1 Food exhibits multi-dimensional features; food plays a role in many contexts, including basic survival, cultural norms, economics, trade, and social situations. We all have a vested interest in food because we all have to eat. Underpinning all of these different roles is the notion that food should be safe. There are many stakeholders, from consumers^[1], to industry, food scientists, farmers, retailers, and regulatory agencies who have different criteria for determining appropriate food choices, leading to trade-offs and tensions in determining the best policy options for food safety systems.
- 1.2 Over the past few decades, the global food supply chain has grown more complex, and breakdowns in food safety have garnered a lot of public attention. There are many notable examples of food safety crises that have ignited public discussion, changed consumer habits, and impacted legislation and industry practices: the bovine spongiform encephalopathy (BSE) outbreak in the United Kingdom, which peaked in 1993 with approximately 1000 new cows being infected weekly (Centers for Disease Control and Prevention 2013a); the Maple Leaf Foods *Listeria monocytogenes* outbreak in 2008, which resulted in 57 confirmed cases and 23 human deaths, partly because the deli meat in question was served to high-risk populations (Birk-Urovitz 2011); and, most recently, the scandal in the European Union when horsemeat was found in prepared foods, such as lasagna and burgers, that were labeled as beef products (Waldie 2013). These all led to demands for new and more stringent production methods and legislation. Food safety challenges have arisen from population growth and an aging population, a global market for food products and global supply chains, increased demand for protein, and climate change pressures on agricultural practices (Newell et al. 2010). These changes in food systems raise policy questions related to the optimal management of risk, which is also tied to food safety at an affordable cost.
- 1.3 In order to investigate these concerns, a basic agent-based model (ABM) has been developed to explore the impact of small changes in system-level rules. Much of the literature examines consumer, industry, or government responses to food safety incidents in isolation; the agent-based model considers the interaction between consumers, retailers, and inspectors. The model is intended to provide insight into these interactions, rather than serve as a predictive tool (Epstein 2008). Three model versions, representing different inspection scenarios, are described using the Overview, Design Concepts and Details (ODD) framework and compared. This paper provides background on the complexity of the food safety environment, the theory surrounding ABMs, employs the ODD framework for describing ABMs, the model results, and conclusions.



Background

- 2.1 The global food safety system is complex: trade, culture, microbiology and spatial and economic aspects all interact to form a system with interdependent elements (Miller & Page 2007, p. 9). As defined by Simon (1962), a complex system is one where "a large number of parts ... interact in a nonsimple way." A distinction must be made here between complex and complicated systems; in complicated systems, the elements within the system maintain some degree of independence and can be studied independently. Complex systems are, by definition, not reducible (Miller & Page 2007).
- 2.2 A contributing factor to food safety's complexity is a lack of certainty; the overall infection and disease burden from unsafe food, even in OECD countries, is unknown (Newell et al. 2010; Rocourt, Moy, Vierk, & Schlundt 2003) and small breakdowns at any stage of the system can lead to widely distributed outbreaks, given the interconnected trade system and extensive movement of people (Havelaar et al. 2010; Newell et al. 2010; Rocourt et al. 2003). Consumers may also assess safety along competing dimensions (Green, Draper, & Dowler 2003); the safety of a food can be defined in the immediate term, for example, food that is not contaminated by bacteria, or in the long-term, as in food that will not cause health problems, such as high cholesterol, in the future. Food safety can also be viewed through the competing lenses of values and science (Nestle 2010): food produced in large, industrialized plants may be free from contamination and therefore considered safe, but consumers may express distrust of a complicated system involving industrialized agriculture, and its associated environmental effects, as well as the concentration of the food industry into the hands of a few very large, powerful companies. As noted by Havelaar et al. (2010), "The consumer demands fresh, tasty, healthy and wholesome food products. Nevertheless, safety is in this framework considered an absolute requirement; placing unsafe food on the market is not an option in the consumer's mind." However, defining exactly what safe food means to consumers can be a challenging exercise.
- 2.3 Food-borne disease, for the purposes of this paper, refers to all diseases caused by consuming food contaminated^[2] by any bacterial, viral, prion, or parasitic

agent (Rocourt et al. 2003). Currently, the overall disease burden of food-borne diseases is unknown (Newell et al. 2010). The Centers for Disease Control and Prevention (CDC) estimates that there are 48 million cases, 128,000 hospitalizations, and 3000 deaths related to foodborne illness annually in the United States; this means that 1 in 6 Americans are sick each year (Centers for Disease Control and Prevention 2013b). The Public Health Agency of Canada estimates that 4 million Canadians, or 1 in 8, are sick each year (Public Health Agency of Canada 2013). These estimates come with many built-in assumptions, and both organizations acknowledge that there is underreporting. Although foodborne disease is caused by a variety of pathogens, including common bacteria such as *Escherichia coli*, *Salmonella*, and *Campylobacter jejuni*, viruses such as Hepatitis A and noroviruses, and parasites such as *Trichinella* and *Toxoplasma gondii*, the most common symptom is diarrhoeal disease. Most cases of foodborne disease are relatively mild, and many people do not view diarrhoea as a serious outcome of disease but rather an inconvenience, which contributes to underreporting of pathogens that cause milder disease (Rocourt et al. 2003). However, in more serious cases, foodborne diseases may result in severe complications or death, particularly among vulnerable segments of the population: pregnant women, young children, immune-compromised individuals, and older adults (Gerba, Rose, & Haas 1996). Given differences with reporting structures and surveillance, it can be difficult to compare data across countries and jurisdictions, since a higher number of reported cases could simply be the result of a better surveillance system and not necessarily from more illnesses (Rocourt et al. 2003).

- 2.4 It should be clarified that the current regime of Hazard Analysis Critical Control Points (HACCP) and risk analysis^[3] (Verbeke, Frewer, Scholderer, & De Brabander 2007), developed over the last 30 years (Phillips 2009), has led to declines in estimated foodborne disease incidence (Centers for Disease Control and Prevention 2013b). One definition of regulation that is applicable here is that it "is the sustained and focused attempt to alter the behaviour of others according to defined standards or purposes with the intention of producing broadly identified outcome" (Black 2002, p. 20, as cited in Havinga 2006). Most of the time, the system works at mitigating hazards, but when it does not, there can be serious illnesses and death, and public trust in the food system more generally is damaged. Changes in production systems and trade present new opportunities for pathogens to proliferate or adapt to new hosts. Food safety policies are often national or regional, but as the system has become increasingly globalized, current management systems of risk analysis and HACCP may be overwhelmed by new pathogens and hazards.
- 2.5 Despite new efforts in testing and safety, no pathogens have been eradicated or contained, and new ones are emerging (Newell et al. 2010). Increasingly, viral pathogens are a food safety concern, as shown by recent Hepatitis A outbreaks in the US linked to frozen berries and pomegranate seeds imported from Turkey (Centers for Disease Control and Prevention 2013c), but global microbiological quality control criteria focus on bacterial counts, which is insufficient for dealing with viral contamination (Newell et al. 2010). The food system is also changing rapidly, challenging current policies.
- 2.6 Rules that inform decision-making are fundamentally different in areas of uncertainty. The perception of risk by people exposed to a hazard tends to be fundamentally different from the technical assessment of risk. When social and psychological aspects are included, consumers tend to consistently overestimate some risks while underestimating others, and they are often keen to listen to negative information while ignoring positive information (Thaler & Sunstein 2008; Verbeke et al. 2007; Yeung & Morris 2001). This has led to a gap between how experts and the general public view food risks, leading to frustration on both sides. Heuristics, or mental shortcuts used to make decisions, are prevalent in consumer decision-making and lead to persistent biases. The availability heuristic, for example, leads people to view events that are recent, dramatic, or otherwise easily recalled as more likely to occur (Tversky & Kahneman 1974). Verbeke et al. (2007) highlight fright and panic elements in the social amplification of risk. Fright is related to the individual's perception of the severity of the risk, and is increased if the risks are perceived as unavoidable or if there are differing stakeholder perspectives on managing the risk. Whether information is perceived as reassuring or frightening depends on one's opinion (Sandman 1994). Panic relates to the perception of risk: for example, how many people are exposed to the risk, whether it is unknown or uncertain, and whether it may come with long-term consequences has differing impact. Since food is a complex area, and a lot of information available may sound uncertain, incomplete, and contradictory (especially online), there is a lot of opportunity for public fear following foodborne illness outbreaks.
- 2.7 The consequence is that while there is now a lower morbidity due to foodborne diseases, more recalls than ever are leading to poor public perception (Kramer, Coto, & Weidner 2005). Outbreaks, due to the nature of our changed food system, tend to be spread out over a wide geographic area due to low-level contamination in processed foods (Rocourt et al. 2003, p. 8) and may require new approaches to dealing with their associated illnesses, in part because of anti-microbial resistance (Newell et al. 2010). As stated by Havelaar et al. (2010) "Due to the nature of microbes and our food chain, measures to ensure food safety have to be implemented on a global scale, necessitating a global approach." Part of this global approach requires interdisciplinary research and new methods to understand and promote food safety from farm to fork in an interconnected, complex system.



Rationale for using Agent-Based Modelling

- 3.1 ABM has been met with enthusiasm in some fields of the social sciences, but has not yet been extensively used in public policy. Although some success has been seen in modeling land use management, public health, and water policy, there have been fewer applications in business and policy analysis (Moss 2008). This is especially true with respect to food policy.
- 3.2 The strength of ABMs is that they provide a way to represent complex systems more simply, by focusing on the system's individuals and their behaviours (Railsback & Grimm 2012). Axelrod (2003) states that most modeling in the social sciences is informed by rational choice theory, not because many scholars feel that its assumptions accurately represent human behaviour, but because it allows for deduction. Adaptive behaviour offers a viable alternative to optimization; but it requires simulation since the consequences of adaptation cannot be deduced. ABM offers an opportunity to relax the assumptions of rational choice theory to more realistically model how individuals make decisions. By using straightforward behavioural rules, ABMs can model decision-making in a more realistic manner.
- 3.3 ABM's ability to deal with heterogeneous populations that can use individual data, rather than aggregate data, is a unique feature with strong application to the social sciences. In many cases, social science problems are dealing with heterogeneous populations where variation is masked by aggregate data. The individual-based perspective marks an important departure from many theoretical positions in sociology and policy studies, which view society as a "hierarchical system of institutions and norms that shape individual behavior from the top down" (Macy & Willer 2002, p. 144). Since people react to changes in their environment, and these reactions can cause further changes, this leads to difficulties in backtracking and applying different solutions to complex problems (Rittel & Webber 1973). Methods that can incorporate change over time and control for these changes are able to more accurately capture social processes, and this is one area where simulation holds a lot of promise.
- 3.4 Although many people consider prediction to be a primary goal of modelling, depending on the data available and the goals of the modeling exercise, it is not the only one. Epstein (2008) notes that there are many other reasons to build models, including explaining a phenomenon, guiding data collection, discovering new questions, illuminating uncertainties and dynamics, demonstrating trade-offs, challenging theory, and opening new opportunities for policy discussion. Importantly, since all models are simplified abstractions, Epstein (2008) notes that "all the best models are wrong. But they are fruitfully wrong." Stylized models that are designed to offer insight to a complex system or problem so that further discussion of policy alternatives, legislative changes, or other adjustments may take place may still be very useful, even if they are incapable of prediction.
- 3.5 Only a few authors have explored food safety using agent-based models.^[4] One example used the BSE outbreak in the United Kingdom as a case study to evaluate public risk perceptions using Cultural Theory (Bleda & Shackley 2012). The archetypes (individualist, hierarchist, fatalist and egalitarian) from Cultural Theory were used to inform assumptions about agent perceptions. Social amplification of risk by the media and trust of government of science were also

incorporated into the model. Verwaart and Valeeva (2011) constructed a model looking at producer decisions for improving animal health practices. The model incorporated economic incentives with social influence and was grounded in the theory of planned behaviour. Tykhonov et al. (2008) constructed an ABM of the trust and tracing game designed to collect data on decision-making behaviour in a food supply chain where there is asymmetric information about food safety and food quality. The model incorporated trading agents, representing producers, middlemen, retailers, and consumers as well as a tracing agent. The agents were separated thrifty, opportunistic, or quality-minded categories, which affected their behaviour. Although it is possible to run experiments with human subjects to collect data on their behaviour in a trust and tracing game, these experiments are very time-consuming. By constructing a model, the authors could figure out which iterations of the game were the most interesting and then conduct these as experiments with human subjects. By incorporating theories of human behaviour with food safety scenarios, these models indicate the potential for advancing ABM in this area.

- 3.6 A concern voiced in the literature involves the scientific rigor and reproducibility of ABMs. Many of the models published in the literature are not described using a standard format that allows for others to reproduce them, making independent replication of results impossible (Richiardi, Leombruni, Saam, & Sonnessa 2006). In order to contribute a reproducible model, a model description following the Overview, Design Concepts, and Details (ODD) protocol is given below.



Model Description

- 4.1 The following section follows the ODD framework (Grimm et al. 2010) to clearly outline the objectives and implementation of a basic food safety inspection model. Using NetLogo (version 5.0.1),^[5] a simulated environment was programmed where consumers, stores, and inspectors interact. One of the goals of the model was to observe the effect of information asymmetry on consumer behaviour. The system-level rules governing these interactions were changed in different versions of the model, allowing for comparisons between the scenarios. Insights from these scenarios can then be used to inform policy discussion.

Purpose

- 4.2 The purpose of this model is to provide insight into the role of information and its influence on the optimal level of inspectors in a food system. To explore this, we compare three search strategies used by inspectors: a random strategy,^[6] one where stores can signal to inspectors and consumers that there is a problem,^[7] and lastly, an adaptation of the signalling stores scenario that includes false positive and false negative signals!^[8]

Entities, state variables and scales

- 4.3 The entities included in the model are stores, consumers and inspectors. Food products and suppliers are assumed to be embedded within the stores. The tick counter is used to keep track of discrete time steps. Each time the 'go' procedure is called, the tick counter increases by one tick. Please see Table 1 for a summary of variables and their descriptions.

State variables

- 4.4 **Patches:** Patches have a variable called 'store'; 100 store patches are scattered throughout the model. All other patches represent empty space. Stores are either contaminated or clean – these are represented by red and green in the model. In the scenario that includes possible errors in store signals, store patches also have a variable for the chance of a false positive or false negative signal, which ranges from .01 to .1.
- 4.5 **Consumers:** Consumer agents are a breed of turtle in NetLogo. There are 2000 of them at the start of the model run.

Table 1: Variable description

Variable name	Description
Range	Consumers use a range of patches within which to search for potential destination stores
Immune system	Consumers have a probability that ranges from 10% to 50% of becoming sick should they land on a contaminated patch
Sick	Consumers become sick if they land on a contaminated store and the random number generated is less than immune-system
Bad store patches	List of stores that have made this consumer sick in the past
Destination	Changes each time step; set to the most suitable store within the consumer's range that is not a member of bad-store-patches
Heal counter	If a consumer becomes sick, it remains sick for 3 time steps and does not move

- 4.6 **Inspectors:** Inspectors have a range within which they look for patches to inspect; this range is twice the range of consumers. The number of inspectors in the model has been varied. Firstly, experiments were run using 1-15 inspectors to get a sense of model outcomes. More detailed experiments were then run using 1 inspector, 3 inspectors, and 5 inspectors, respectively.
- 4.7 **Minimal spatial element:** Consumers and inspectors both have a range within which they can see potential destinations. There are no collectives in the model. Simulations last for 150 time steps (or ticks, in NetLogo); the length of one time step is not specified, given that this is a highly stylized model. However, in a real system, the relevant time step would be days.

Process Overview and Scheduling

- 4.8 Once the model is set up, the following processes, described under submodels, are executed in the following order.

- One store per time step is randomly selected and becomes contaminated.
- In the model versions with store closures, stores that have not been visited in 10 time steps close.
- Consumers execute their consume procedure, as follows:
 - Destination-set
 - Consumers evaluate all stores within their range, and choose a store patch that is not on their list of bad-store-patches. If no such store exists, the consumer wanders by randomly setting its heading and moving forward three patches.

- Eat

- If the store is contaminated and the random-number generated is less than immune-system, the consumer becomes sick and adds this patch to the list bad-store-patches. The consumer also sets its heal counter to 1.

- If the consumer is sick, it does not execute the above two procedures, but instead adds 1 to its heal-counter.

- Inspectors test

- The testing procedure varies depending on the complexity of the model version.
- In this most basic model, inspectors move randomly to a store within their range. If the store happens to be contaminated, the inspector changes the contaminated variable from 1 back to 0 and changes the store's colour to orange. If the store is not contaminated, the inspector does nothing.
- In the 'stores signal' scenario, 5 stores per time step are selected to signal; if they are contaminated, they turn pink, which lets consumers know to avoid the store and lets inspectors know to come check it first.
- In the 'stores signal with errors' scenario, 5 stores per time step are selected to signal. If the store is contaminated and a random floating point number is greater than the store's 'signal-error' variable, then the store signals. If the floating point number is smaller, then the store will not signal even though it is contaminated (a false negative). As well, if the selected store is not contaminated, but the random floating point number is less than the store's 'signal-error' variable, then the store will signal even though it is not contaminated (a false positive.)

- Consumers that have been sick for three time steps heal.

- 4.9 Since there are no collectives in the model, the order in which each consumer, inspector or patch executes the above is not important. For a summary of the three scenarios, see Table 2.

Design Concepts

- 4.10 A number of concepts and theories underlie the model's design, and they have been used to influence the variables and the submodels used in the model.
- 4.11 Basic principles: The following basic principles, adapted from the literature on food safety, have been incorporated into the model.
- 4.12 Embedded supply chain: In the model, suppliers and producers are embedded and only stores are explicitly shown in the model. Since consumers only interact with stores and restaurants, and they bear the brunt of responsibility for supplying 'safe' food products, this element greatly simplified the construction of the model. The literature also supports this point: "When major food safety issues arise, both retailers and manufacturers will be affected (if not harmed) by any recall, even if they are not to blame for the problem" (Grievink, Josten and Valk 2002, p. 481-2, as cited by Havinga 2006).
- 4.13 Inspection system: In the Canadian context, the Canadian Food Inspection Agency is responsible for enforcing policies set by Health Canada that govern the safety of food sold in Canada; the CFIA fulfills this mission by inspecting federally-governed abattoirs and food processing plants. When food safety emergencies occur, the CFIA responds along with Health Canada, provincial ministries, and industry; food recalls are coordinated by CFIA staff. The CFIA is also responsible for enforcing laws on labeling and packaging, regulating products derived from biotechnology (although Health Canada is responsible for assessing the safety of new foods) and certifying exports and initial import inspections of food and agricultural products, among other responsibilities (Government of Canada 2013). Provincial governments are responsible for provincially-licensed abattoirs, which can only sell meat in the province in which they are licensed. Restaurant and food service inspection is quite fragmented, and is generally carried out by municipalities, regional health authorities, or the provincial government, depending on the province (Government of Canada 2014). Although products sold in grocery stores and restaurants have generally been inspected further up the supply chain, these inspections are not represented in the model. The model presented in this paper most closely mirrors the inspection of restaurants and food service outlets.
- 4.14 Immune system: This is one area where there is no real answer in the literature. Although there have been advancements in predictive microbiology, a method used to predictively model pathogen spread, persistence, and death in a food source (Lammerding & Paoli 1997; Walls & Scott 1997), this research does not provide a clear translation of how pathogen loads in a food source affect the actual occurrence of illness.^[9] Certain groups, such as the elderly, young children, pregnant women, and immune-compromised people are more susceptible to foodborne pathogens than others (Gerba et al. 1996), but there is uncertainty as to the actual likelihood of illness from consuming contaminated food products. As such, model runs were completed using an immune system parameter that is heterogeneous and varies throughout the population between .1 and .5.
- 4.15 Consumer avoidance: Previous research conducted by the Food Standards Association in the UK indicates that, if they had concerns about hygiene, up to 70% of respondents would not purchase again from a food service outlet (as cited by Choi, Nelson, & Almanza 2011). As well, focus group research from the UK has indicated that personal experience with food poisoning is an important source of knowledge for changing food safety behaviour, and some quoted participants indicated that getting sick after eating specific products from a supermarket meant that they would never return (Green et al. 2003). Since the literature did not provide adequate explanation of what factors would influence a consumer to return to a food service outlet where they believed they had contracted an illness, this concept was simplified for use in the model: consumer agents will not return to stores where they have become sick in the past.
- 4.16 Store signals: It is possible for a store to close temporarily and trigger an investigation from inspectors if it realizes that there is a problem with its food. For example, during the 2012 XL Foods *E. coli* outbreak, a Regina restaurant called Flip decided to close its doors when five people reported cases of *E. coli*, and the only common feature with all five cases was that they had recently eaten at Flip (CBC News 2012a). Although the restaurant had recently been inspected and had passed, the owner voluntarily closed the restaurant to keep any other customers from becoming sick while the source of the contamination was determined. This element has been incorporated as a signalling mechanism, where stores change their colour to communicate with inspectors that they should be inspected first and so consumers can avoid that location until the contamination has been rectified.
- 4.17 Store signals with errors: On occasion, stores with a suspected problem may choose to ignore it and not close; there is also the possibility that a store will close unnecessarily. The restaurant Flip, as mentioned above, closed temporarily to undergo thorough testing, which found no *E. coli* present on surfaces or food samples (CBC News 2012b). This has been represented in the model by stores signalling with a small chance of either a false positive or false negative signal. This allows for less than perfect information in signalling, which reduces the efficiency of inspections.
- 4.18 Asymmetric information: This principle is informed by Akerlof's (1970) work on asymmetric information in markets. Consumers and inspectors are unable to tell if a store is contaminated prior to landing on it. An interesting application of this theory in future models would be to incorporate signals of quality, such as branding, inspection certificates, or other quality assurance methods.
- 4.19 No consumption while sick: Given the typical symptoms of diarrhoea and vomiting that accompany foodborne illness, the assumption that one would stay home and avoid going out to stores or restaurants seems reasonable. This was also implemented for practical modeling reasons, as it prevents a consumer from landing on a contaminated store and becoming sick while already infected from a previous visit.
- 4.20 Emergence: The important results from the model are the overall numbers of sick agents, contaminated stores, inspected stores, and "naïve" agents at the end of the model. Since the changes between model versions are imposed by changes in the rules that agents follow, the results are built in and not the result of

emergent behaviour.

- 4.21 Adaptation/learning: Consumers adapt their behaviour by updating the list bad-store-patches. If they have gotten sick from eating at a contaminated store, they add this store to the list and avoid this patch in the future (even if the store has since been inspected and it is no longer contaminated). Consumers also avoid signalling stores.
- 4.22 Objectives: Consumers want to avoid getting sick, and this fits into their adaptive behaviour of avoiding stores that have made them sick in the past. Store patches want to avoid contamination, and if that is not possible, avoid making consumers sick by signalling – although this is imposed. An implicit assumption is that inspectors should inspect efficiently; again, the different inspection strategies are imposed, rather than allowing the agents to choose which they prefer.
- 4.23 Sensing: Inspectors and consumers have the same sensing capabilities: both types of agent can sense when a patch is signalling, and they can tell whether a store is contaminated once they land on it. However, landing on a contaminated store may make consumers sick, but inspectors can reverse the contaminated variable so that the store is safe again. Consumers cannot sense whether a patch has recently been inspected or whether consumers near them are sick.
- 4.24 Interaction: At this stage, neither consumers nor inspectors interact with one another directly. Consumers interact with stores by visiting them (although other consumers may be present there at the same time) and consuming, and inspectors interact with stores.
- 4.25 Stochasticity is used in generating a random number to determine whether or not the consumer will get sick. Also, if consumers complete the 'wander' procedure, they determine a heading randomly and move three patches in that direction. Prediction is not used. There are no collectives, or "aggregations of agents that affect the state or behavior of member agents and are affected by their members" (Railsback & Grimm 2012, p. 41), in the model.
- 4.26 Observation: The following attributes are tracked using BehaviorSpace at each time step. This output was then analyzed in R (version 2.15.1)
 - The number of agents that are sick (indicated by brown agents in the model)
 - The number of signalling (pink) stores at any one time
 - The number of contaminated (orange) stores that inspectors inspect
 - The number of stores that stay contaminated (red)
 - The number of "naïve" consumers (those that have never gotten sick over the course of the model run, indicated by yellow agents)

Initialization

- 4.27 Model runs were executed with 2000 consumers, 100 stores, and 1, 3 or 5 inspectors. The world was set to 33x33, for 1089 total patches, with a centre origin point. The world wraps both horizontally and vertically. Each simulation was run for 150 time steps; in earlier tests that measured runs at every step, the model appeared to stabilize by the 150 step mark.
- 4.28 To determine the appropriate number of consumers and stores, simulations were run at various levels of stores and consumers. The actual density of food service outlets is about 1 for every 350 Canadians (Statistics Canada 2006). However, approximating this density in NetLogo would have a prohibitive time cost; running very large simulations in BehaviorSpace is extremely slow. To balance the effects of scaling up with the time cost of running multiple scenarios, 2000 consumers and 100 stores were included in the model.
- 4.29 Consumers: All consumers have immune-system set to between .1 and .5, sick set to 0, heal-counter set to 0, and range set to 5. The lists destination and bad-store-patches are empty. Consumers are scattered randomly throughout the world. In future work, consumers will be made more heterogeneous, but at this point, they are all the same at the start of the model.
- 4.30 Patches: 100 patches are selected, and store is set to 1. All store-patches have the contaminated variable set to 0 at initialization.
- 4.31 Inspectors: All inspectors have a range of 10. They are scattered randomly throughout the world.
- 4.32 Most of these initial values were estimated, as there is little empirical data available. No data was incorporated from other models or external data files.

Submodels

- 4.33 Consumers: "Healthy" consumers are asked to complete the consume procedure; consumers that are sick must remain on their last destination for 3 time steps. The consume procedure contains two sub-procedures: destination-set and eat. To destination-set, consumers identify which patches within their range are stores that are not on the list bad-store-patches (and are not signalling that they are contaminated, depending on the model version). They then choose one of these destinations from the patch-set and move there. If no patches within their range meet the criteria, the consumer wanders by setting their heading randomly and moving forward three patches. In the eat procedure, the consumer identifies whether or not the patch they have landed on is contaminated. If it is contaminated and the random number generated is less than the consumer's 'immune-system,' the consumer's sick variable changes to 1 from 0 and the consumer changes its colour to brown, then adds this patch to the its list bad-store-patches. All consumers execute this code in a random order. More than one consumer can land on a store at the same time.
- 4.34 Inspectors: Inspectors are asked to complete the test procedure. Depending on the model version, the inspector is instructed to test any signalling (pink) stores within its range first, since these ones are signalling that they may be contaminated. Otherwise, the inspector chooses a store within its range at random and checks it. When the inspector lands on a store that is contaminated, it changes the store's contaminated variable back to zero and changes the patch colour from red (or pink, if it was signalling) to orange. If the patch is not contaminated, the inspector does nothing.
- 4.35 Patches: Only patches that are stores and belong to the agent-set 'store-patches' will be discussed here. All other patches simply represent empty space. Store patches all start out green to indicate that they are not contaminated, and one store per turn is instructed to change its contaminated variable to 1 from 0 and its colour to red. Agents cannot sense this information prior to landing on the store, unless the store is pink to signal contamination. In versions that incorporate signalling, five patches per time step are instructed to check themselves for contamination. If a selected patch is contaminated, it signals this to consumers and inspectors by changing its colour to pink. In the scenario that allows for signals with errors, the signal procedure incorporates a random floating point number. If the store is contaminated and the random number is less than its 'signal-error' variable, the store will not signal even though it should, and if the patch is not contaminated but the random number is less than its 'signal-error' variable, the store will signal, even though it is clean.

Table 2: Model versions

	Baseline	Signal with certainty	Signal with errors
Consumers	Avoid "bad stores"	Avoid "bad stores" & signalling stores	Avoid "bad stores"& signalling stores
Inspectors	Test randomly	Test signalling stores first; if none in range, test randomly	Test signalling stores first; if none in range, test randomly



Analysis of model results

- 5.1 Initially, all model scenarios were run with the number of inspectors ranging from 1-15. The marginal returns of adding additional inspectors are minimal once there are five inspectors in the model; therefore, more detailed runs were conducted using 100 repetitions each of one, three, and five inspectors. Each model run lasted for 150 time steps and all data was collected at the end of the model run. Analysis of variance (ANOVA) was conducted to check the statistical significance of having one, three, and five inspectors for each scenario, and was followed by post-hoc analysis using pair-wise t-tests, using the Bonferroni correction to account for multiple comparisons. Unless otherwise stated, the pairwise analysis results are statistically significant ($p < .001$).
- 5.2 The first scenario is the most simple; inspectors move randomly from store to store and consumers receive no information besides whether or not they become ill. The number of sick consumers declines substantially as the number of inspectors goes up, but with decreasing marginal returns (see Table 3). As well, the number of contaminated stores decreases as inspectors are added, and the number of inspected stores increases, again with decreasing marginal returns. The decrease in contaminated stores is likely fueling the declines in the number of sick consumers. Lastly, the number of naïve consumers increases as there are more inspectors in the model, but even with five inspectors, only a very small percentage (1.2%, on average) of the total population never experiences an illness over the course of the model run.

Table 3: Random Inspection Scenario

	1 inspector		3 inspectors		5 inspectors		ANOVA	
	Mean	SD	Mean	SD	Mean	SD	$F(1,298)$	p -value
Sick Consumers	499.22	38.41	310.21	38.02	227.48	35.36	1807	$p < .001$
Contaminated Stores	49.02	3.86	26.24	3.06	17.03	2.69	2463	$p < .001$
Inspected Stores	29.47	3.36	51.97	3.84	60.62	4.09	1947	$p < .001$
Naïve Consumers	0.91	1.627	8.35	3.83	25.66	10.58	633.2	$p < .001$

- 5.3 The next step in advancing the model was to allow five randomly selected stores per tick to signal. This signalling mechanism would be similar to a store realizing that there was a problem and voluntarily closing its doors and inviting in inspectors to help rectify the issue. In this scenario, signalling information is perfect; that is, a signal indicates that the store is definitely contaminated. The results of this scenario are shown in Table 4.
- 5.4 Since inspectors move first to signalling stores within their range and consumers avoid these stores, even though very few stores were self-testing at any given time, the number of sick consumers was considerably reduced compared to the random inspection model. The effect of signalling information is profound: outcomes are better with only one inspector when there is signalling (209.8 sick consumers, on average), compared to having five inspectors conducting random inspections (227.48 sick consumers, on average). Inspectors are also able to control the number of contaminated stores more effectively, particularly when there are few inspectors. Increasing the number of inspectors from 3 to 5 shows that the effectiveness of the signal mechanism is subject to considerable decreasing marginal returns, likely because the inspectors' ranges begin to overlap and a signalling store could end up with more than one inspector there at the same time. In the case of signalling stores, there was no significant effect in post-hoc testing ($p > .05$) of increasing the number of inspectors from three to five, even though the overall ANOVA results were still significant. The number of naïve consumers also increases compared to the random inspection scenario, but even with five inspectors in the model only about 6% of the total population, on average, avoids becoming ill over the course of the model run. This is an interesting result; it is possible that the density of consumers to stores and the frequency of visits are such that it is nearly impossible for consumers to avoid illness throughout the simulation. To investigate further, it would be necessary to measure whether consumers become ill frequently throughout the simulation, and also to run additional experiments varying the ratio of consumers to stores.

Table 4: Stores Signal with Certainty

	1 inspector		3 inspectors		5 inspectors		ANOVA	
	Mean	SD	Mean	SD	Mean	SD	$F(1,298)$	p -value
Sick Consumers	209.8	39.24	161.32	30.67	136.63	30.04	231.6	$p < .001$
Contaminated Stores	20.57	2.55	11.92	2.22	9.21	2.15	883.4	$p < .001$
Inspected Stores	57.61	3.62	66.16	3.75	68.6	3.97	368.8	$p < .001$
Naïve Consumers	34.69	11.22	74.39	18.12	120.52	25.61	992.5	$p < .001$
Signalling Stores	5.09	2.12	0.44	0.61	0.17	0.4	439.5	$p < .001$

- 5.5 Finally, a scenario was constructed to investigate the impact of imperfect information in store signals. This variation on the stores signal scenario included errors: when stores are selected to signal whether or not they were contaminated, there is a chance between 1% and 10% that a 'clean' store may signal, or that a contaminated store may not. In this variation, there were slightly more sick consumers, on average, compared to the version with perfect signalling information, as well as slightly higher levels of contaminated stores and lower levels of inspected stores. However, the difference between the two scenarios shrinks as more inspectors are added. Once again, in the case of signalling stores, there was no significant effect of going from three to five inspectors in post-hoc testing ($p > .05$), even though the overall ANOVA results were still significant. Table 5 shows the results for the scenario with stores signalling with errors.

Table 5: Stores Signal with Errors

	1 inspector		3 inspectors		5 inspectors		ANOVA	
	Mean	SD	Mean	SD	Mean	SD	$F(1,298)$	p -value
Sick Consumers	223.55	37.37	168.63	26.64	139.81	31.72	327	$p < .001$
Contaminated Stores	23.58	2.45	13.06	2.11	9.72	2.12	1224	$p < .001$
Inspected Stores	48.26	4.11	55.55	4.33	58.7	4.31	287.4	$p < .001$
Naïve Consumers	26.22	8.39	63.04	17.52	103.72	25.21	890.3	$p < .001$
Signalling Stores	9.1	3.04	0.87	0.97	0.29	0.57	574.1	$p < .001$

- 5.6 To check for a significant effect of scenario type while controlling for the number of inspectors present, analysis of variance was conducted. Post-hoc analysis using pair-wise t-tests was also completed. Unless otherwise stated, the pairwise analysis results are statistically significant ($p < .001$). The ANOVA results are reported in Table 6.

Table 6: All three scenarios

	1 inspector		3 inspectors		5 inspectors	
	ANOVA	p -value	ANOVA	p -value	ANOVA	p -value
Sick Consumers	$F(2,297)$	$p < .001$	$F(2,297)$	$p < .001$	$F(2,297)$	$p < .001$
Contaminated Stores	1812	$p < .001$	666	$p < .001$	252.5	$p < .001$
Inspected Stores	2678	$p < .001$	1013	$p < .001$	350.1	$p < .001$
Naïve Consumers	1494	$p < .001$	343.6	$p < .001$	161.8	$p < .001$
	465.5	$p < .001$	575.5	$p < .001$	547.8	$p < .001$

- 5.7 The post-hoc analysis showed that as inspectors are added, the difference between the scenarios shrinks; this is especially true for the stores signal with certainty and stores signal with errors scenarios. When there is one inspector, the difference in the number of sick consumers between stores signalling with certainty and stores signalling with errors is significant ($p < .05$), but with three inspectors, the results are not statistically significant ($p > .05$) and with five inspectors, they are identical ($p = 1$). As well, with three inspectors, the difference in the number of contaminated stores is significant between the stores signal with certainty and stores signal with errors scenarios ($p < .01$), but once there are five inspectors, the results are no longer significant ($p > .05$).
- 5.8 Figure 1 shows the differences in the number of sick consumers for all three scenarios. The considerable difference in the number of sick consumers in the signalling scenarios compared to the random inspection scenario is clearly shown, as is the diminishing marginal returns of adding additional inspectors.

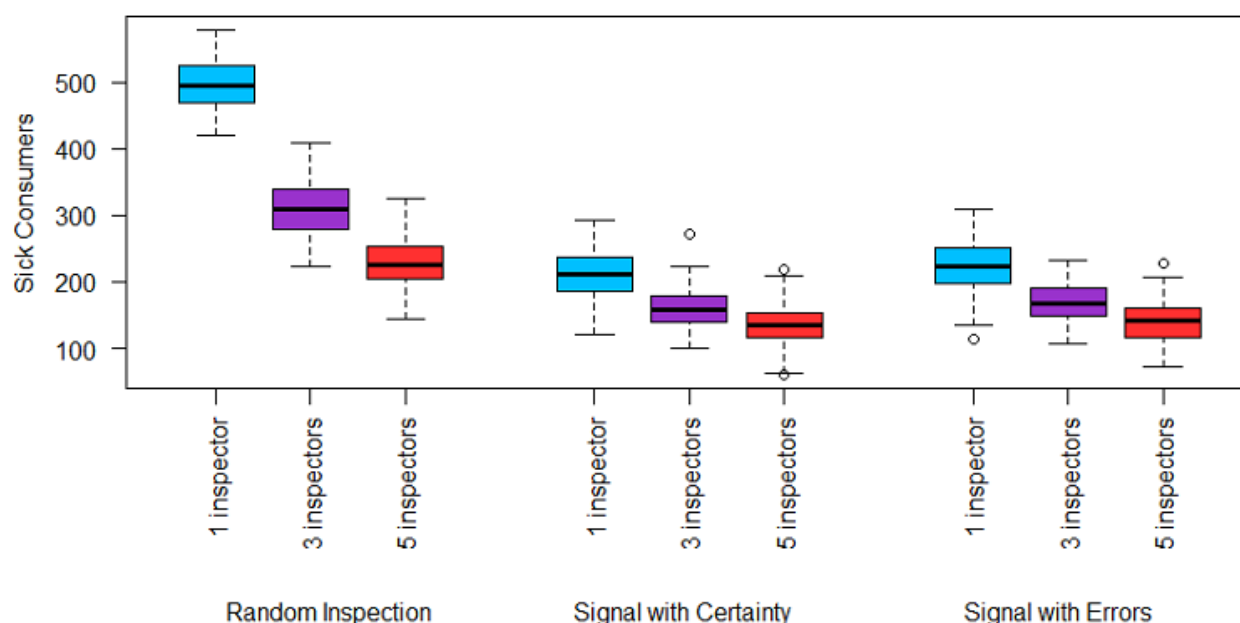
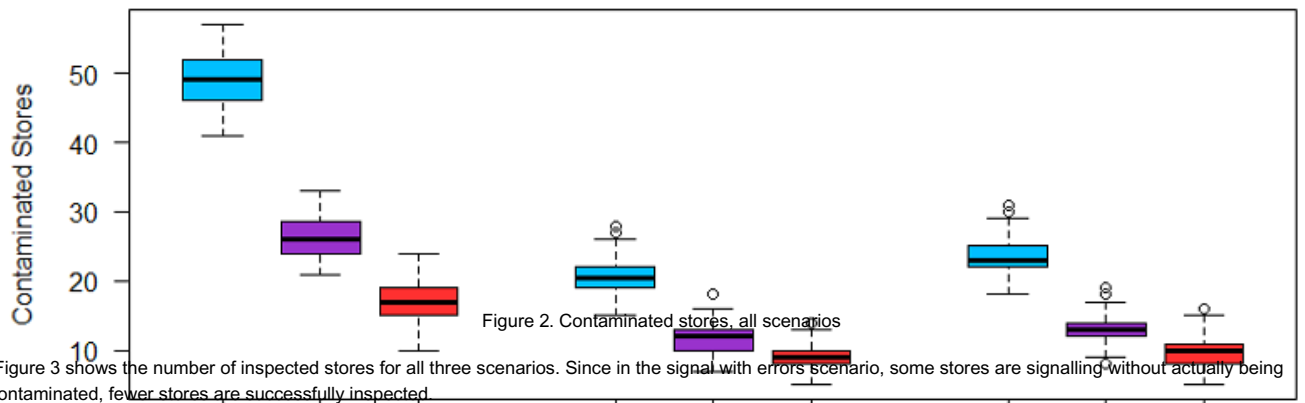


Figure 1. Sick consumers, all scenarios

- 5.9 Figure 2 shows the number of contaminated stores for all three scenarios. Giving inspectors more information through signalling, even if that information is flawed, considerably reduces the number of contaminated stores.



5.10 Figure 3 shows the number of inspected stores for all three scenarios. Since in the signal with errors scenario, some stores are signalling without actually being contaminated, fewer stores are successfully inspected.

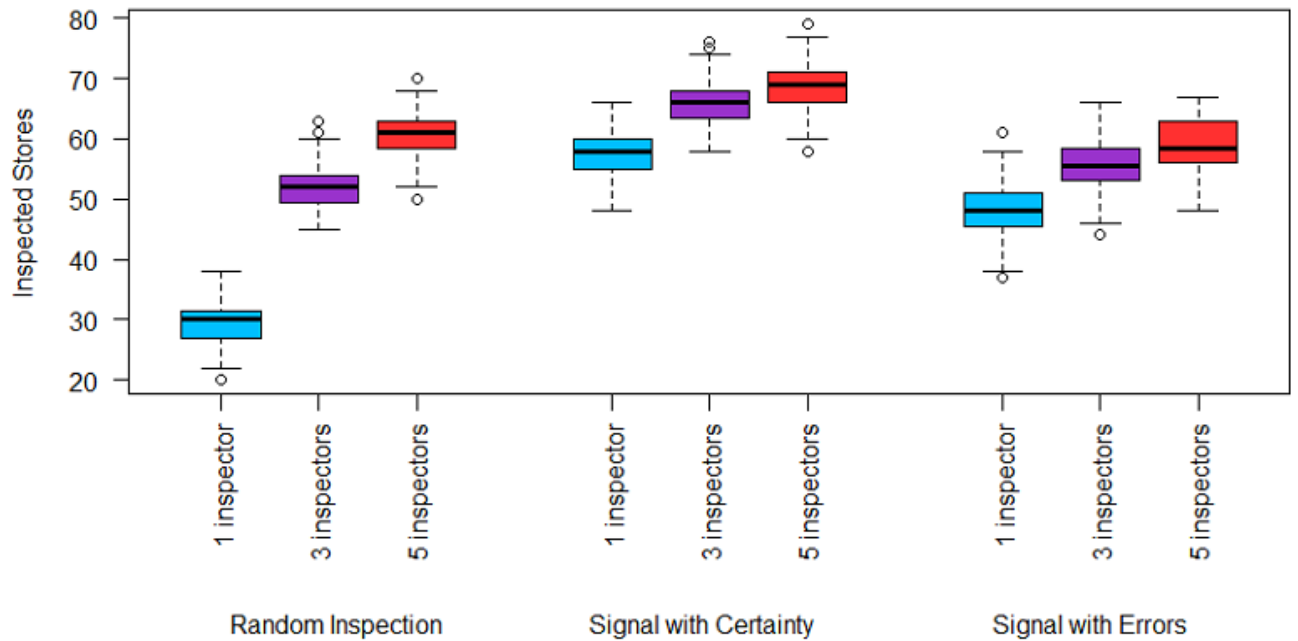
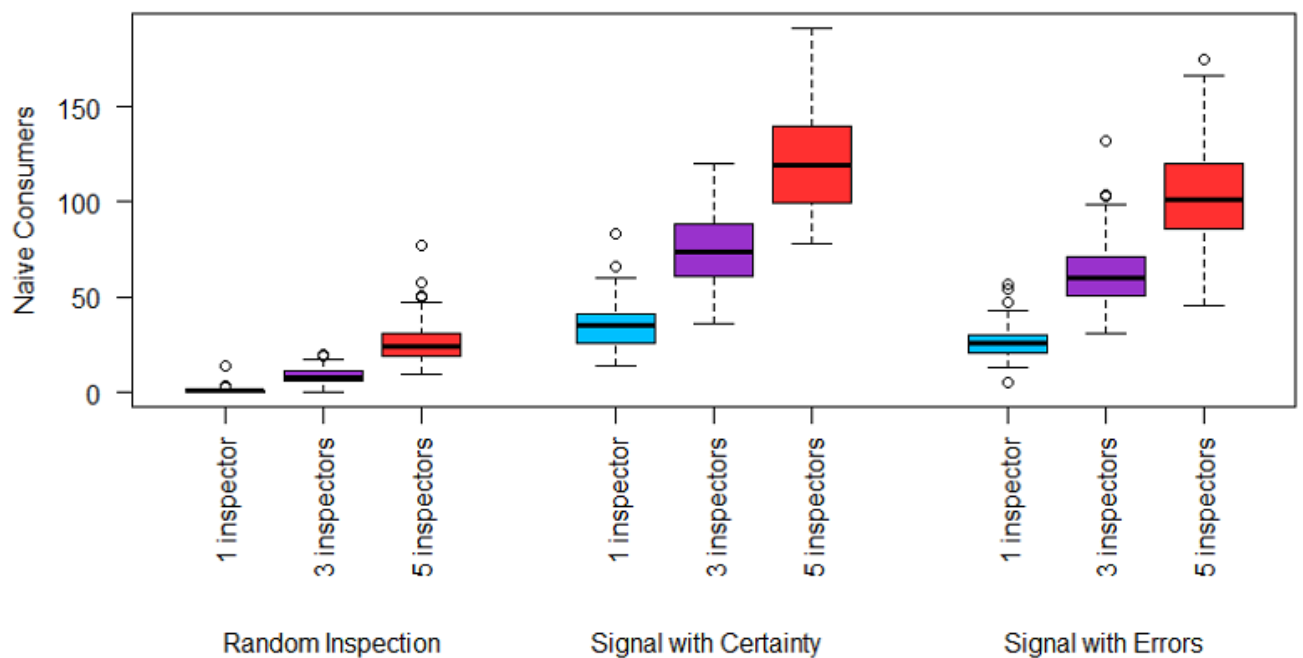


Figure 3. Inspected stores, all scenarios

5.11 Finally, Figure 4 shows the number of naïve consumers for all scenarios. Since consumers avoid stores that are signalling under the assumption that they are contaminated, fewer consumers become sick over the course of the model run in the stores signal with certainty scenario. However, when stores signal with errors, some stores that are contaminated should signal but do not, which results in slightly more consumers becoming ill at some point during the model run.





Discussion and conclusions

- 6.1 The above research shows that food safety is a complex problem, and that ABMs are an interesting way of studying complex problems. A simple model of a food safety system was presented using the ODD framework. The model results have a few applications to policy. Firstly, as stated by Bonabeau (2002) and Moss (2008), ABMs were noted as having great potential for policy but had been applied in only a few situations. This model advances the literature by providing a model that incorporates inspectors, consumers, and stores into a food safety simulation. Only a handful of other models have been found in this area (Bleda & Shackley 2012; Tykhonov et al. 2008; Verwaart & Valeeva 2011). The model results also show the effect of giving inspectors and consumers more information: even if the information provided by stores signalling is uncertain, the outcome of having one inspector with access to imperfect signalling information (223.55 sick consumers, on average) is similar to five inspectors using random inspections (227.48 sick consumers, on average). In the current climate of government austerity, employing new means of improving consumer and inspector access to food safety information could improve outcomes without taxing already thin resources.
- 6.2 There are a number of avenues for future work using this model. Namely, the model should be adapted to better take advantage of the strengths of ABM by incorporating more heterogeneity and complexity into individual agents. As well, inspection rules that are closer to the real world system, such as a tiered system of oversight which is used by the Regional Health Authorities in Saskatchewan and has been proposed by the CFIA (Canadian Food Inspection Agency 2012), will be incorporated in future work, as will the influence of retailer compliance on outcomes. Some jurisdictions have also made inspection results public, giving consumers more information with which to make decisions on where to eat (Filion & Powell 2009; Simon et al. 2005); the effect of this information on decision making will be used to inform future models. Green et al.'s (2003) work on the social meanings of food choice, the influence of social norms on decision making, and the role of information in social networks could be incorporated by including communication between neighbouring agents to share information on experiences with the safety of certain food outlets.
- 6.3 In his work discussing New Public Management, Hood (1991) discusses three sets of core values in public management: sigma (efficiency), theta (fairness), and lamda (robustness). He characterizes sigma values as most closely related to New Public Management, where frugality is the standard of success and waste is the standard of failure. For theta values, the achievement of fairness is the standard of success and unfairness or bias is the standard of failure. Lastly, for lamda values, resilience is the standard of success and catastrophe, risk or breakdown is the standard of failure. These value sets apply to food production systems as well as to public management. In many supply chains, the tendency of business interests is to lean towards sigma values, where efficiency is king. However, as supply chains increase in complexity and change ever more rapidly as more actors are involved in the production and distribution of food, a movement towards greater resilience may be warranted,^[10] even as this results in redundancies. As noted by Miller and Page (2007), a certain level of redundancy in complex systems may make them more readily adaptable. The balance of valuing efficiency or resilience is another trade off within the food policy space, as Hensen and Caswell (1999, p. 591) note: "Rather, it is evident that policy is the outcome of a complex trade-off between alternative demands that reflect the interests of the different groups that might be affected. In the case of food policy this will include consumer, food manufacturers, food retailers and farmers, both at home and abroad, as well as government itself and taxpayers. One of the key challenges facing policymakers is to balance these alternative demands because, in many cases, these different groups apply alternative criteria, both when judging the need for food safety regulation, ex ante, and the success/failure of food safety regulation, ex post. Furthermore, these criteria are generally not explicitly stated, with the result that the policy debate lacks coherence and, in some cases, transparency." Complex problems, if they are to be effectively handled by regulatory structures, require transparency and information shared between all stakeholders. Agent-based models that incorporate transparency, accountability and information exchange may be a useful source of insight for accomplishing these objectives.



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The feedback and comments provided by Drs. Peter Phillips and James Nolan on an earlier draft of this paper are acknowledged. This research was supported by a Doctoral Fellowship provided by the Social Sciences and Humanities Research Council of Canada.



Notes

¹For a more detailed discussion, see Smith DeWaal 2003.

²Contamination by chemical hazards or environmental pollution is beyond the scope of this study.

³For a more detailed discussion, see Schlundt 1999.

⁴Another ABM study looking at compliance and pig farmers is available in Dutch (van Asselt, Osinga, Asselman, & Sterrenburg, 2012).

⁵NetLogo is available here: <https://ccl.northwestern.edu/netlogo/>

⁶View this model in the CoMSES Model Library: <https://www.openabm.org/model/4137/version/2/view>

⁷View this model in the CoMSES Model Library: <https://www.openabm.org/model/4141/version/2/view>

⁸View this model in the CoMSES Model Library: <https://www.openabm.org/model/4139/version/2/view>

⁹One such example that was decided by the courts took place in the United States, where FSIS tried to shut down a processing plant that had exceeded Salmonella counts. The plant refused on the basis that the product had come contaminated from the slaughterhouse, and the plant never failed any sanitation tests. A federal judge ruled that FSIS could not withdraw inspection based on Salmonella counts alone: "The appeals court ruling supports arguments of those who say that pathogen testing results should not be a basis for enforcement actions until scientists can determine what constitutes a unsafe level of Salmonella in ground meat" (Rawson & Becker 2004).

¹⁰This sentiment is echoed by Hennessy et al. (2003), who comments that narrow technology development platforms that may not be able to adapt to changes may introduce systemic risk into food production.



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