An Agent-based Model of Food-borne Diseases Under Climate Change Scenarios in Mexico City

The Risk of Street-food in a Warming City

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Abstract: Food is a conventional vehicle for pathogens to reach and infect new hosts. Distinctively, street food is a major source of food-borne diseases and climate change effects will intensify this by increasing the mean surface temperature and thus, the microorganisms growth rate. Through this research we present a preliminary agent-based model that simulates at various levels the dynamic of street-food consumers and food-borne disease under climate change scenarios, using tunable parameters such as hygiene level, microorganisms growth rate and number of consumers. The results show that the model has the potential to be a useful tool for optimizing decision-making and urban planning strategies related to health and climate change.

1 INTRODUCTION

Street food is an array of food characterized by its preparation and consumption in public places i.e. parks or streets (Von Holy and Makhoane, 2006). It is generally affordable and conveniently located near the working district in cities, which makes it the most accessible source of food for people in lower and middle socio-economic positions (FAO, 2011). Regardless of consumers being aware of the low hygienic standards of the stalls and the vendors unsanitary cooking practices (Bakic H., 2014), the working class finds street food more affordable and less time-consuming in comparison to eating in a restaurant or bringing food from home (Duhau and Giglia, 2007).

The street food stalls have been present in Mexico City since ancient times. However, it was at the end of the XIX century that great rates of migration from rural to urban areas, driven by economic opportunities, increased the diversity and proliferation of this particular activity (Barbosa C., 2010). Street food vending in Mexico City is also an economic response to the low employability rates and salary, representing a large portion of the informal economy (Duhau and Giglia, 2007) and constituting a large source of income for families in lower socio-economic positions(WHO, 2010). Nonetheless, this ancestral cultural food source is disregarded by the government and continues to be part of the informal economy and in consequence an antecedent of food-borne diseases.

Food has been through time a conventional vehicle for pathogens (bacteria, virus, parasites) to reach and infect new hosts (Newell et al., 2010) and according to WHO (2010), the improper infrastructure of the street food stalls and the inadequate handling of the food are the principal drivers of the microorganisms growth and thus food-borne diseases. Combined with the lack of piped water, street vendors generate improper sanitation practices that promote food contamination. In addition, the lack of electricity to refrigerate food in the informal food stalls enhances the growing rate of microorganisms leading to risk-setting-levels of bacterial population in the food. Hence, the microbiological safety of food remains a dynamic situation heavily influenced by multiple factors along the food chain from the farm to the fork (Newell et al., 2010), placing higher health risks among the most vulnerable groups i.e. children, elderly and immunocompromised population.

Moreover, food-borne disease will be intensified by climate change through multiple factors impacting food safety including: changes in temperature and precipitation patterns (Tirado et al., 2010). In addition, climate change will also affect socio-economic aspects related to food systems such as: agriculture, global trade, demographics and behavioral lifestyles which influence food safety (Newell et al., 2010; Tirado et al., 2010). In consequence, climate change, the increasing transient human population, global markets and antibiotic resistance will turn food-borne diseases into a global health threat. However, this research will focus only on the environmental conditions the food is cooked, sold and consumed. Other steps in the supply chain will be disregarded.

The current anthropogenic climate change is shifting the spatial distribution, range and intensity of climate parameters such as temperature and precipitation. In the street food consumption context, changes in mean temperatures will intensify the street food-borne diseases by intensifying the microorganisms growth.

Laboratory research on different species of bacteria have demonstrated that their growth rates increase proportionally with temperature, within a range of 0° C and 70° C (Acai et al., 2015; Alvarez-Ordones et al., 2008; Schaechter et al., 1958). All within the range of surface air temperatures in Mexico City. Therefore an increase of the surface temperature in Mexico City would lead to augmenting rates of bacterial growth in street food. The projected surface temperature in Mexico City under the four representative concentration pathways (Van Vuuren et al., 2011) is expected to escalate on average from 1 to 5°C by 2100.

2 MODEL DESCRIPTION

Our model was created using Netlogo (Wilensky, 1999) and it represents the dynamic of a typical working area in Mexico City during lunch time. It is a sample of 100 persons (agents) that move through different street-food stalls (food-patches) each day. Each food-patch has a different level of microorganisms that could potentially get sick to the persons that consume their food, and the microorganism levels grow as a function of the mean daily temperature (Figure 1).

Each simulation is ran for 36500 times-steps under the four different climate change scenarios, representing a projection of the number of cases in the next one hundred years.

The variables of the model are: the overall *Hygiene* of the street-food stalls, the *growth rate* value of the microorganisms as a function of temperature, and the *climate change scenario* that will determine the temperature evolution through time.

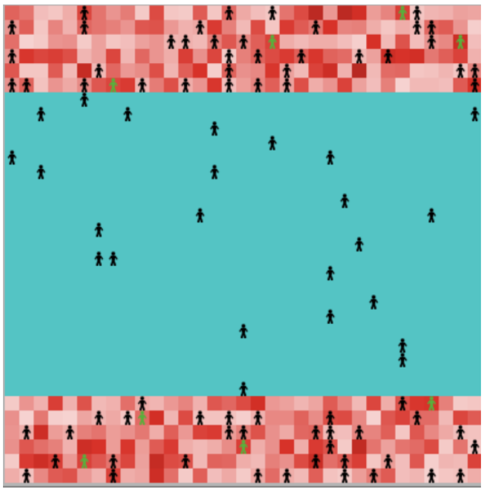

Figure 1: Agent-based model world with agents (black figures), street-food stalls (red patches) and neutral area (blue patches).

2.1 Street-food Stalls Representation

The stalls are represented by the red patches of the ABM (Figure 1). Each stall patch has a parameter that describes the amount of microorganisms in the food, which is given by

```
ask food-patches [
   ifelse random 100 > Hygiene
   [
   set level_micro random-normal-in-bounds (100
       - Hygiene) 10 0 100
   set pcolor 19 - (7 * level_micro) / 100
   ]
   [
   set level_micro random-normal-in-bounds 5 5 0
       100
   set pcolor 19 - (7 * level_micro) / 100
   ]
 ]
```

The variable `Hygiene` is a user dimensionless input, which is used to set the level of microorganisms in each food-patch. The function `random-normal-in-bounds a b c d` take a random number from the normal distribution with mean value a, standard deviation b and inside the bounds $[c,d]$. `pcolor` sets the intensity of red as a function of the microorganisms level. The latter is truth for the patches that comply with the condition `random 100 > Hygiene`, all other food-patches have microorganisms levels given by `random-normal-in-bounds 5 5 0 100`.

The level of microorganisms will grow as a function of temperature as represented below

```
set growth 1 + micro growth rate * temp
ask food-patches [
set level_micro level_micro * growth
if level_micro > 100
[set level_micro 100]
set pcolor 19 - (7 * level_micro) / 100 ;;
]
```

The variable `micro growth rate` is a user defined value that represents how much the microorganisms growth as a function of the mean daily temperature (`temp`).

Moreover, the microorganisms level is restarted every seven days, representing that on weekends the street-food stalls re-supply their food with the base level of microorganisms than before.

2.2 Temperature Scenarios

The temperature evolves through the time given the climate change scenario chose by the user. The temperature scenarios were obtained by the mean values over Mexico City of the CMIP5 models (Taylor et al., 2012) under the RCPs 2.6, 4.5, 6.0 and 8.5 (Van Vuuren et al., 2011). In order to work with a simple expression for the temperature evolution, we obtained the polynomial equations that fitted the temperature data. Moreover, in order to simulate the seasonal dynamic, we added to the polynomial equations a sine wave with amplitude of $2°C$ and noise given by `random-normal-in-bounds 0 1 -10 10`.

2.3 Illness Representation

Each time step certain amount of `consumers`, defined by the user, is positioned in a food-patch, where it is going to compare its `immunity` to the level of microorganisms. If the level is greater than the agent immunity, then it will be considered to get sick. This computation is done using random numbers from the normal distributions as shown below

```
ask turtles [
   ifelse consumers > random 100
   [ move-to-empty-one-of food-patches]
   [move-to-empty-one-of work-patches]
 ]
   ask turtles-on food-patches [
     ifelse level_micro > random-normal-in-bounds
         immunity 10 0 100 [set sick 1
        set ill ill + 1
        set color green]
      [set sick 0]
     ]
```

3 EXPERIMENTS

Several experiments were performed with the model in order to test its scope and limitations. Since the aim of this model is to be used as a decision-making tool given the specific conditions of the population to be modeled, it is important that our model responses make sense.

We used data from a previous study performed in Mexico city (Estrada-Garcia et al., 2002) in order to set the hygiene level on the model. The hygiene level was set to 60% for all the experiments, meaning that around 40% of the street-food stalls have a microorganisms level M generated by the normal distribution `random-normal-in-bounds 40 10 0 100`, the rest 60% had a microorganisms level around 5. The immunity of the persons was set to 60, meaning, that they need a level of 60 microorganisms in the stall in order to get sick.

One of the main variables that should be calibrated according to the specific pathogens that cause the main food poisoning in the population of interest, is the microorganism growth rate as a function of temperature. This growth rate is defined in section 2 and can be rewritten as $M = M * (1 + mgr * T)$ where M is the level of microorganisms, mgr is a microorganism growth rate scalar and T is the daily mean temperature.

The mgr scalar changes the intensity in which temperature impacts the number of food poisoning cases. Figure 2 shows the number of food poisoning cases as a function of mgr and controlling for all the other parameters. In this case, the temperature scenario was the RCP8.5, and it can be seen that the temperature trend is shown only until mgr is greater than 0.004. As many studies have shown, the temperature is an important controlling factor for the pathogens' growth rate (Duan et al., 2015; Ratkowsky et al., 1982; Koseki and Isobe, 2005), so in the following experiments we will use $mgr = 0.004$.

Moreover, as stated in section 2, our model has the ability to represent the temperature seasonal cycle over the climate change signal. This cycle, as pointed out by some authors (Yoshikura, 2015), is a very important driver of the internal dynamic of food poisoning and bacterial growing. Figure 3 (top) shows historical data from 2010 to 2015 of surface mean temperature and total food poisoning cases in Mexico City, as it is observed, there is a correlation and the peaks of both variables match. The bottom panel of the same Figure shows the results of our model when its used with the seasonal cycle and o climate change signal, as it is observed, the number of cases follow a similar pattern than the historical data, which

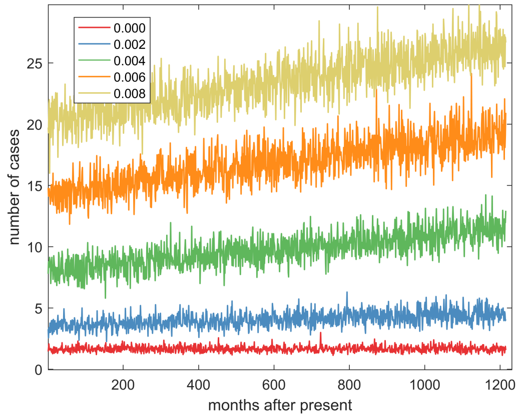

Figure 2: Number of food poisoning cases for different model sensitivities to temperature.

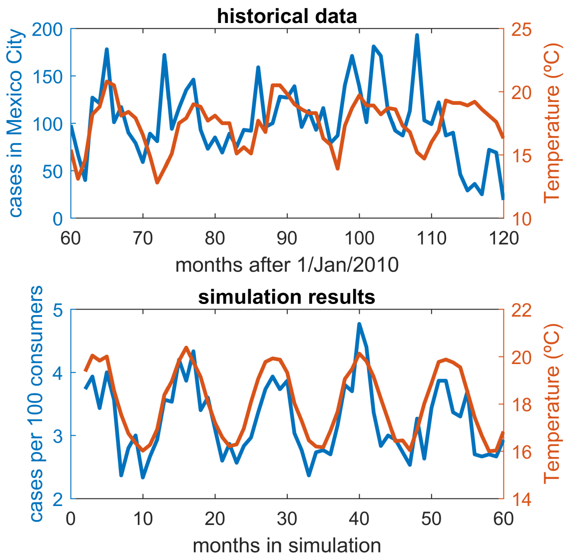

Figure 3: Seasonal behavior of the historical data (top) compared with simulation results (bottom).Food poisoning historical data: (SS, 2017), climate historical data: (CONAGUA, 2017).

is caused by it's dependency to the seasonal cycle.

The model was forced using the temperatures correspondent to the mean values of the four RCP climate change scenarios over Mexico City. Figure 4 shows the mean value of daily food poisoning cases of a year per 100 consumers, as it is shown, the difference between the climate change scenarios is clearly distinguishable after the first couple of decades. It is important to notice that the values are the average of the daily cases, which means that a difference of 1 would imply a 365 persons difference over a year.

Finally, the variable `consumers`, that represents number of street-food consumers could be adjusted by

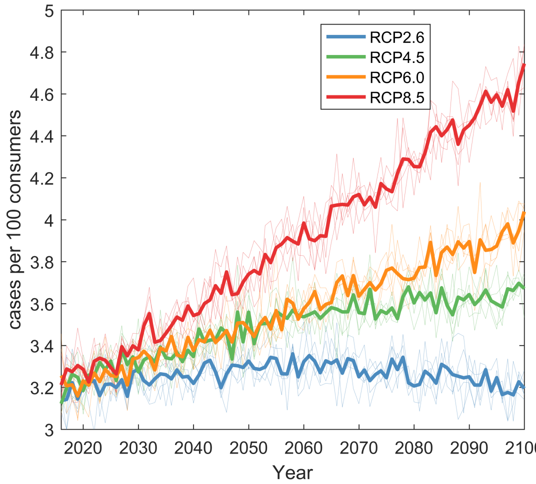

Figure 4: Average number of daily food poisoning cases per 100 consumer under four climate change scenarios. The solid lines show the mean values of 5 simulations per scenario.

the specific population that is going to be modeled, in these experiments we used 100 out of 100, but this can be change according the estimation of persons that have lunch in street-food stalls in the population that the user wants to represent.

4 DISCUSSION

In this work we proposed a preliminary set of interconnected gears that could potentially represent a process-based bottom-to-top model of the food poisoning dynamic in a city that will get warmer over time. Although we used the Mexico City's temperature projections, it would be necessary to adjust the microorganism growth rate and the number of street-food consumers in order to get a real useful simulation of Mexico City's specific population.

As shown in Figure 2, the model is highly responsive to the microorganism growth rate as a function of temperature. In that sense, it is necessary to specify the the species of microorganisms that most affect the population of interest and obtain its specific growth rate curve using laboratory data. Therefore, the *mgr* parameter would be adjusted to use in an specific population. Moreover, the microorganisms growth rate might be affected by other factors that should be implemented in future versions of the model, such as access to public toilets, running water and electricity for food refrigeration.

Also, as it is observed in Figure 3, the seasonal cycle is a strong driver in the number of food-poisoning cases. In these experiments we made up the seasonal cycle with a sinusoidal wave and noise, however, it is possible to use the general circulation models' results as data that directly feed the model temperature parameter in order to have more realistic estimations. An added benefit of doing so would be the representation of the frequency and intensity of heat-waves, which are also determinant in food-poisoning peaks.

The model is also able to change the number of consumers out of 100 persons. Thus, it can be seen as a parameter of the socio-economic level of the population that the user wants to simulate.

Finally the hygiene parameter is crucial in the model. It will determine the initial microorganisms levels. Hygiene levels is a variable we can control for and one which local decision-makers have influence on. Therefore, in hygiene relies the opportunity for improvement by increasing access to piped potable water, public toilets, electricity and health promotion education.

The lack of accurate and longterm monitoring data on aetiology and occurrences of food-borne diseases was the main limitation for a further validation of this model. The rates reported were taken from the available Mexican morbidity data reported monthly from 2007 to 2015, so this would only be used to validate the present behavior as done in Figure 3. Validation of the climate change signal reflected in the diseases would not be possible due to the short period of time retrieved. However, other important issues could be pointed out in the future such as the reflection of heat-waves on the diseases rate.

Future research might involve also the precipitation parameter to describe better the proper environment for microbial growth. Also, it is important that the parameters are calibrated according to the health inequalities of the population that the user wants to simulate such as socio-economic status, gender, ethnicity and age. Additional, efforts should be placed in reducing underestimation of cases (due to lack of self-report) and biologically recognizing the aetiology of the disease.

5 CONCLUSIONS

The model presented here was constructed using research in several fields such as microbiology, health, urban dynamics, and climate change. It is known that climate change will enhance the rate of change of several processes, in this case, by scaling up the basic influence of temperature in microorganisms growth, which adding up to the dynamic of a global-south socio-economic vulnerable population, will result in a greater health risks than the health sector might be prepared for facing.

Historically, the street food business has been very flexible and is able to adapt very quickly to economic realities. Therefore, with the correct utilization of models like this, street food adaptation and mitigation projects should not represent an unreachable challenge.

It is common for the global south to adopt knowledge coming for research in other countries. Nonetheless, that knowledge does not always reflect the complex reality that people live in middle and low income countries. For that reason, our model allows the user to calibrate the parameters according to the population of interest.

Finally, future work will include important spatial dynamics that will make the most of the utilization of ABM to this particular problem, such as the representation of actual public urban spaces where street-food consumption takes place. Also, agents will count with individual decision mechanisms in order to avoid previously visited stalls whose food made them sick.

The ultimate goal of this project is to have a model that incorporates information of the state-of-the-art results on public health, microbiology, urban dynamic and climate change, which would be of great importance in a city from the global south that has limited budget to face climate change effects in the incoming decades.

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