Investigating the Public Health Burden of Campylobacteriosis: A System Dynamics Policy Analysis

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Abstract

Campylobacter affects nearly 100.000 people each year in the Netherlands, and costs the Dutch economy millions of euros in costs from chronic illness. *Campylobacter* is spread to humans through various environmental and foodborne links, and it is likely underdiagnosed, which has made it a resilient problem to tackle in the past.

We aim to understand if climate change will result in more *Campylobacter* infections and increase its hidden burden, to bring attention to the problem and analyse policies to tackle it. System Dynamics proved a good tool for it, and we found that most policies tested were robust across different scenarios, albeit not cost effective. The most promising results came from limiting environmental transmission, which is also expected to show increased relevance with climate change. This provides a starting point to further analyse proposed solutions and reduce the effect of *Campylobacteriosis* on the Dutch economy and healthcare system.

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1 Introduction

Campylobacter is regarded as a central cause of foodborne diseases in Europe (European Food Safety Authority & European Centre for Disease Prevention and Control, 2019). Despite this, its economic impact has been understudied. The European Food Safety Authority estimates that the costs of sickness and the cost of loss of productivity caused by the pathogen is around € 2.4 billion a year in the European Union.

Common symptoms of a *Campylobacter* infection (called campylobacteriosis) include diarrhoea, abdominal cramp, nausea, vomiting and fever (Hussein et al., 2016). For people with weakened immune systems due to underlying medical conditions, such as AIDS or cancer, this *Campylobacter* may cause a life-threatening infection (Wassenaar & Blaser, 1999).

Economic impacts of food-borne illness - a societal challenge

2019 estimates suggest the total number of Campylobacteriosis cases in the Netherlands was around 73,000 (Lagerweij et al., 2020). However, due to its mild symptoms, it is speculated that a significant amount remained unreported (Koutsoumanis et al., 2020). Considering gastroenteritis is most commonly caused by *Campylobacter* (Fouts et al., 2005), and 98 cases of gastroenteritis per 10,000 were reported in the Netherlands in 2016 (van Pelt, 2016), a better approximation may be around 100-150 thousand people, resulting in possible cost of illness of at least 21 million euros in the Netherlands (Havelaar et al., 2005).

The Netherlands may be spending millions of euros on fighting preventable symptoms. Once infected, people might work at a sub-optimal level, take sick leave or need to see a doctor. The municipal health service (GGD) may even have to set up an investigation in accordance with the Dutch contingency plan for infection control, "Draaiboek Uitbraken van gastro-enteritis en voedselvergiftiging".

Campylobacteriosis represents a threat to public health because of its individual and societal consequences, not to mention the impact on healthcare costs and the Dutch economy. Therefore, the implementation of effective preventative interventions is a significant societal challenge for the Netherlands.

The main cause of human infections occurs through food-borne transmission via consumption of poultry (Wilson et al., 2008). *Campylobacter* are highly adapted to live and colonise the intestinal tracts of avian species and other mammals. (Saif & Barnes, 2008). For farm-kept poultry, contamination can occur at all stages of the production chain. The pathogen spreads due to contact with infected faeces and other litter, either through human or insect contact. The periodic partial depopulation of the flock, a.k.a. "thinning", further contributes to this spread. The processes within slaughterhouses also lead to (cross-)contamination of carcasses, which is how *Campylobacter* ultimately lands on surfaces of meat products sold to consumers (Skarp et al., 2015).

Vertical transmission amongst chickens (i.e. from parent to offspring) seems to not play a significant role in the continued proliferation of *Campylobacter* (Callicott et al., 2006). Instead, horizontal transmission routes via the environment are seen as a major culprit of the spread between flocks. While *Campylobacter* grow optimally at range of 37–42 °C in anaerobic conditions, they can survive *ex vivo* in water (Wilson et al., 2008). This means various disease vectors such as insects, mice and other vermin that come into contact with contaminated water or faeces, can greatly contribute in the spread of the pathogen (Newell & Fearnley, 2003).

Despite implementation of containment/control measures, the number of positive tests has increased EU-wide since 2017. While this is partially a consequence of member states expanding monitoring on *Campylobacter*, it underscores that health and economic impacts still require attention (Nastasijevic et al., 2020).

Why is System Dynamic used?

To study these effects, Systems Dynamics (SD) was used. This is a sub-discipline of computer modelling that focuses on causal relations between factors and analysing how these give rise to feed-backs, accumulations and delays over the whole system or within smaller sub-systems. System dynamics centres on the belief that system structures cause the behaviours observed in socio-technical systems (Pruyt, 2013). System dynamics is thus a suitable choice for the modelling of *Campylobacter* transmission and its healthcare and economic impacts due to the ability to test policy choices in the form of changes to system structures and causal relationships.

There are several examples of system dynamics modelling applications to address health-related issues including public health challenges of obesity (Chen et al., 2018) and Kawasaki's disease (Huang et al., 2013).

Research question and knowledge gap

The lack of experimental data on *Campylobacter*'s transmission routes and the subsequent ability to analyse *Campylobacter*'s impact on the economy constitutes a fundamental knowledge gap. To address this, we have formulated the following research question:

What are the economic impacts of Campylobacter under different climate, population, and public health scenarios, and what policy measures can address these?

To measure the extent to which system objectives are realised, we use the following three Key Performance Indicators (KPIs): The amount of contaminated chicken meat and the number of environmental transmissions, which affect the final KPI: cost of illness. The first two allow us to assess to what extent the different sub-models affect the final dependent variable under different scenarios and interventions.

This project is part of the course EPA1341 Advanced System Dynamics. The project expands upon prior research conducted on the topic of *Campylobacter*. Adding to existing research, this work explores the economic impact of policy measures aimed to prevent the spread of *Campylobacter* and the effect of climate change. The programming environment of Vensim is used to analyse these dynamics.

In this paper, we represent a comprehensive model to assess the impact of *Campylobacter* on the Dutch economy. We start by explaining the conceptualisation, validation, and experimental setup of our model in Chapter 2, which paves the way for the development of interventions and gives insights into the statistical significance of each transmission route under different circumstances. The results of the possible interventions ran under several scenarios are presented in Chapter 3. Finally, we present and discuss our findings and their implications in Chapter 4.

2 Methods

This chapter details the processes and decisions underlying the composition of the model used to answer the research question. Model specification, settings, validation and verification, and experimental setup are established.

2.1 How is System Dynamics used?

An essential aspect of system dynamics models are accumulations, delays and feedbacks (Sterman, 2001). This is suited to the system we wanted to model, and appropriate variables were chosen to represent these features. Infected populations of humans and chickens are modelled as stocks, whilst various transmission routes provide flow variables between them. Feedback loops are modelled as the number of contaminated chicken flocks causes more spread of *Campylobacter* in the environment, and more chickens are infected. Delays are present both in the dynamics of contamination and in implementing policies to slow or suspend transmission.

2.2 Conceptualisation

The model focuses on public health and economic impacts associated with *Campylobacter*-contaminated chicken meat. The dynamic hypothesis includes three KPIs that were examined to answer the research question:

- **Contaminated Chicken Meat**: part of the infected chicken submodel. This KPI is expected to increase with worsening climate conditions and no interventions.
- **Environmental transmissions via disease vectors**: expected to increase with worsening climate conditions that reinforce disease vector prevalence and reinforce transmission routes, and decrease when vectors diminish.
- **Cost of illness**: is expected to increase with increasing *Campylobacter* infection rates, and decrease (at different rates) with the introduction of different policies.

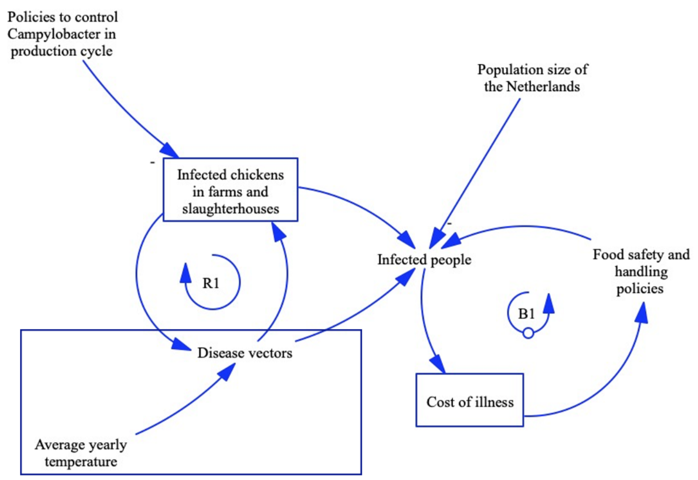

Figure 1: The aggregated causal loop diagram for the dynamic hypothesis

Model Structure

Conceptualisation of the model structure is shown in Figure 1. The model focuses on farms and slaughterhouses collectively, rather than individual types of farms. This aligns better with decision-making regarding the aggregate impacts of policy choices across the entire poultry industry in the Netherlands. This aggregation level excludes most of the internal processes of slaughterhouses and broilers, as these are too detailed for this scope. Furthermore, this model does not use age cohorts because the public health and cost of illness metrics already incorporate age weightings (Mangen et al., 2007).

Model Boundaries

This model draws wider boundaries than Rommens' original model (Rommens, 2020). This work focuses on climate, population, and policy effects (both on production and consumption) and the subsequent economic impacts of these factors. Moreover, with the internal components of the farms and slaughterhouses simplified, this allows for more focus on environmental transmission pathways.

The sub-model of 'Infected Chickens' encompasses the relevant features of this original model (Rommens, 2020). The following sections detail model structure and behaviour.

Dynamic Hypothesis

This conceptualisation informed the dynamic hypothesis for behaviour of KPIs, shown in Figure 2.

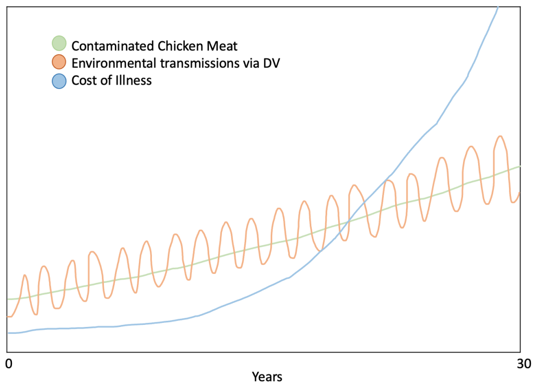

Figure 2: Dynamic hypothesis for the KPIs

It is hypothesised that the amount of contaminated chicken meat slowly increases over time because of the reinforcing loop between the chickens and the disease vectors. Secondly, it is expected that the effect of disease vectors follows the temperature as one of the disease vectors (flies) is prevalent during the warmer months. Along with climate change, this slowly increases over time as well. Thirdly, the cost of illness increases exponentially as the chronic cases accumulate over time.

2.3 Model Explanation

This analysis contains three main sub-models: environmental transmission, infected chickens and cost of illness.

Environmental

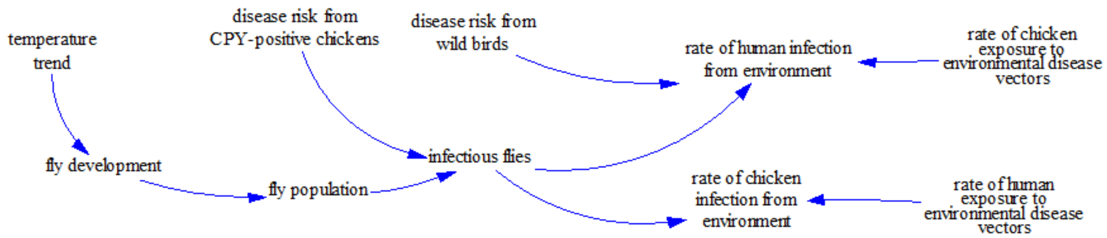

Figure 3: Diagram of the environmental sub-model

The main biological disease vectors have been determined to be flies (Mughini-Gras et al., 2016). Flies are considered to be major spreaders as they actively excrete *Campylobacter* on surfaces and human food (Berndtson et al., 1996; French et al., 2009; Hald et al., 2008). We use the common house fly as the model organism to represent the effects of disease vectors (Hald et al., 2008). Skovgård et al., 2011 suggests that flies are mainly short distance carriers of *Campylobacter*. Therefore, the risk of transmission by flies particularly high when the populations are greatest, which is during summer (Royden et al., 2016). Hald et al., 2007 showed that preventing flies from entering houses in the summer of 2006 caused a significant drop in the prevalence of *Campylobacter* at farms. Climate change will cause the number of flies in the Netherlands to increase in both summer and winter (Goulson et al., 2005). Rainfall is not a driving factor in the size of the fly population (Goulson et al., 2005), and so was excluded from the model as an environmental factor.

An increase in Dutch population size is not expected to increase the fly biomass in the Netherlands (Guenat et al., 2019). Even though an increase in the population leads to more organic waste (Garcia-Garcia et al., 2015), which does have the potential to increase the total number of flies (Imai, 1984; Rozendaal, 1997), this effect is possibly counterbalanced by the loss of natural habitat.

Infected chickens

Figure 4 shows the conceptual dynamics of transmission and contamination in farms, broilers and slaughterhouses (Rommens, 2020). Healthy chickens become infected with *Campylobacter* due to environmental disease vectors (Royden et al., 2016), which themselves become infected from chicken (Skovgård et al., 2011). These infected chickens then become contaminated chicken meat when slaughtered. They can also cause cross-contamination, making the meat of healthy chicken also potentially contaminated when it enters into contact with the bacteria (Berndtson et al., 1996). Consumption of contaminated meat may then cause human infection (Wilson et al., 2008).

This submodel behaves like the "success to the successful" archetype (Pruyt, 2013), where the feedback loops around the rate of chicken infection imply that when there are fewer infections, it is prone to stay that way. However, when infections rise, it is difficult to limit their growth. The implications for our model is that a slight push in the direction of infections can have significant implications.

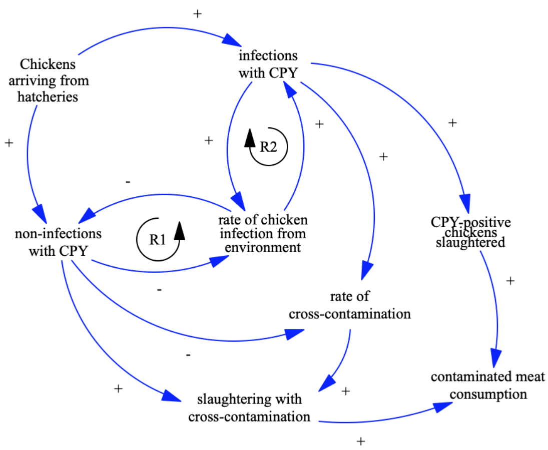

Figure 4: Conceptual causal loop diagram for chicken infection and contamination

Other internal variables in this model included probabilities of infection, which are determined by environmental factors such as propagation of disease vectors, with the exact values for these rates detailed in Appendix 4.3.4.

Cost of illness

The cost of illness associated with *Campylobacter* infections is modelled and calculated based primarily on a 2007 study by Mangen (Mangen et al., 2007). The Infected Persons stock is split off into symptomatic and asymptomatic infections. Symptomatic infections are assumed to all develop acute gastroenteritis, with a proportion of all cases recovering or subsequently developing chronic illnesses. Each of these outcomes contribute to public health metrics of Disability Adjusted Life Years (DALYs) for these infections and the Cost of Illness for all *Campylobacter* infections.

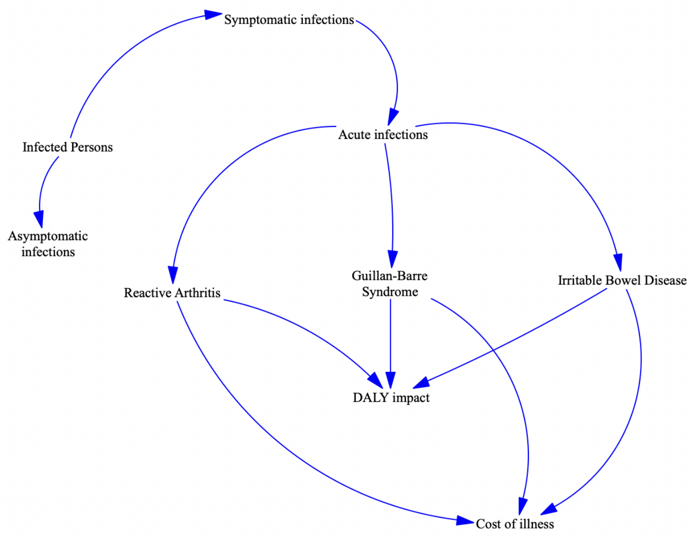

Figure 5: The conceptual Cost of Illness sub-model

The causal structure adopted for this sub-model focuses on connecting variables based on available scientific data. Due to the underlying complexity of DALYs and Cost of Illness metrics (Jo, 2014), we take a top-down approach to applying these variables. As such, variables have been used for some elements in place of stocks (e.g. DALYs and Cost of Illness). This simplistic approach is considered appropriate as we are not concerned with the details of transmission and recovery, but only with the ultimate KPI 'Cost of Illness'.

2.4 Key Assumptions

The main assumptions made in modelling these causal structures are:

- All chicken meat consumed in the Netherlands is produced in the Netherlands and the Dutch population cannot eat more than is produced.
- All infected meat becomes contaminated meat when slaughtering.
- Cross-contamination in the slaughtering process depends on the proportion of total infected chickens present at the moment of slaughtering.
- The development of chronic disease is assumed to always occur subsequent to a case of acute gastroenteritis (in reality, some cases develop chronic disease without first developing gastroenteritis, following a *Campylobacter* infection
- There is no recovered population, meaning that infected people are able to be reinfected and do not become immune.

2.5 Model Specification

The main equations of note employed in each submodel are detailed in Table 1.

Table 1: Important equations in each submodel. All functions are over t, which signifies the time step.

Submodel	Equation	Description
Infected Chickens	$A(t) = B(t) + C(t) \times a$	Contaminated meat $A(t)$ with $B(t)$ the function of CPY-positive chickens slaughtered, $C(t)$ a function of slaughtering with cross-contamination, and a the meat per chicken-contaminated meat-consumption, a variable used to modify a stock to change units from 'chicken' to 'kg' in the stock flow structure.
Environmental Transmission	$D(t) = a + E(t)$	Fly development rate $D(t)$ with a being the base development rate of flies and $E(t)$ a function of fly population growth per °C.
Cost of Illness	$F(t) = G(t) \times b \times \frac{p(t)}{t}$	Symptomatic infections $F(t)$ with $G(t)$ the stock of *campylobacter* cases, b the rate of symptomatic cases, $p(t)$ is a rectangular pulse with the width of the time step that has a rectangular pulse around the 52nd week of each year. $p(t)$ thus empties values from the stock once per year.

A complete list of variables and parameters used in the model are detailed in Appendix 4.3.4.

2.5.1 Modelling software used

The system was modelled using VenSim PLE software developed by Ventana Systems Inc.

2.5.2 Integration method

Euler was considered an adequate integration method for this model as it is suitable for integrating over non-linear and discontinuous functions (such as the pulse trains used to drain some stocks), and it is a simple a direct method of integration. However, it does present some limitations in computational inefficiencies.

2.5.3 Time step

The time step must be small enough such that the derivative of the model is constant between two points close in time. A Time step of 0.0625 was selected, as behaviour of the model was consistent with that of lower time steps (see Figure 6).

Results of this model are presented starting at the 53rd week (1 year and 1 week through the simulation). This is to allow for the model behaviour to be stabilise, since all stocks are given initial values of zero. This also allows for behaviour to be reported starting in the year 2021.

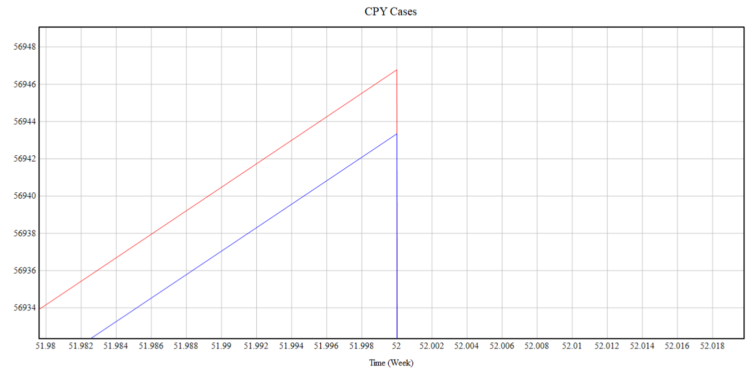

Figure 6: Peak CPY Cases with time steps 0.0625 and 0.03125

2.5.4 Time period

The time period of 30 years (1560 weeks) was chosen to be able to show the effects of incremental changes in climate variability, however, since the impact of worsening climate conditions is tightly linked to seasonality, the time unit was weeks.

2.6 Model Verification and Validation

In this subsection the model was subjected to several verification and validation. Verification was done through a comparison with the conceptualisation of the model, as well as a unit and a time step verification.

2.6.1 Verification

To verify the conceptualisation, the causal diagram construed in chapter 2.2 was compared with the model built. There have been some addenda to the model, but the functions still match.

Units were checked to ensure consistency with real-world equivalents. The only noteworthy unit is that of the flow *Symptomatic infections*. The model's time unit is set to *week*, to facilitate seasonal temperature throughout the year. As DALY and COI are reported per year, a PULSE TRAIN function is modelled between stocks *CPY Cases* and *Acute GE Cases* to convert time units. This accumulates all *Campylobacteriosis* cases over 52 weeks before transferring them to the cost of illness submodel. This 'transforms' the unit into years for the COI submodel. The units of the PULSE train remain in weeks when the time unit should be thought of as year, as happens after.

The time step verification was performed by running the model at several different time steps. The time step 0.0625 is chosen so the integration method (Euler) is valid. When halving the time step, we found that model returned similar model behaviour,

2.6.2 Validation

Several tests were performed to ascertain whether the model was fit for purpose (Forrester & Senge, 1980). The complete Validation (including visuals) can be found in Appendix B.

Before presenting the conclusions of our validations, let us emphasise that the model is mostly conform the dynamic hypothesis: our interpretation of how the system's structure results in behaviour, with some minor differences. All submodels interact with each other as expected. Visualisations and commentary on model performance relative to the dynamic hypothesis is given in Section 3.1.

Appendix B also elaborates on the model boundary. The model boundary determines the kind of policies that can be tested, and vice versa: the policies we were interested in shaped the model boundary. We included the pathways we deemed interesting for our research question, and the tests we have performed are only concerned with these pathways.

We first explored the extremes of these boundaries: to what parametric changes is the system sensitive? The first and most obvious boundary is regarding time, as the *final time* of the model cannot be higher than 30 years, since information such as temperature increase due to climate change and population projections are only defined until that date. Other extreme conditions tested can be found in table 2.

Table 2: Variable values used for extreme conditions testing and test results.

Variable	Extreme low	Extreme high	Result
Temperature increase by 2050	-1	25	Model breaks under extreme high condition, but behaves as expected under extreme low.
Initial fly population	0	1	Model breaks under extreme high condition, but the data from the first year has already been deemed inaccurate, thus, the model could still be used. The model behaves as expected for extreme low.
Chicken arriving from hatcheries	Halved	Doubled	Model breaks under extreme high condition, but behaves as expected under extreme low.
Infections per kg of meat consumed	Halved	20x	Model breaks under extreme high condition, but behaves as expected under extreme low.
Base infectious flies	0	0.8	Model breaks under extreme high condition, but behaves as expected under extreme low.
Base chicken exposure rate	0	0.8	Model breaks under extreme high condition, but behaves as expected under extreme low.
CPY reproduction in chickens	0	4	Model breaks under extreme high condition, but behaves as expected under extreme low.

Next, we conducted multiple sensitivity analyses. We found that the system is fairly reliable when in the univariate tests. The results of the multivariate sensitivity analysis showed that there is quite some numeric sensitivity. This is mainly due to people changing their consumer behaviour, and meat piling up as a result.

Finally, we compared our model to real world data, and made the following observations:

- The number of people with campylobacteriosis is slightly higher in the model than in the estimates, but the difference is within an acceptable range.
- Most of the cases of campylobacteriosis originate from the environment and not from poultry consumption, conform to literature.
- The proportion of infected chickens in the base model corresponds to the expected proportion in the real world.

- The model calculates more DALYs than the literature, which may be an indication that doctors are sometimes unable to trace the diagnosis back to *Campylobacter*.
- The Cost of Illness is lower than the literature. This is probably due to the fact that we only look at acute cases and three chronic diseases. The values used are also indexed to prices from the year 2000. It's recommended that model users apply an institutionally appropriate inflation figure.

2.7 Experimental setup

To answer our research question, experiments were set up around the three components in the research question: climate, population and public health.

We identified a number of uncertainties in the model that are summarised in Table 3. Parametric uncertainties were used to perform sensitivity analysis in the model, whereas most structural uncertainties were explored to define possible policy interventions.

Table 3: Summary of uncertainties in the system

Type	**Parametric**	**Structural**
Population	Population projections	Chicken consumption behaviour Food safety in handling
Climate	Temperature projections	Climate effects of temperature seasonality Pest control measures to limit spread of disease vectors
Public health	Cost of illness Proportion of people developing chronic illness	Slaughterhouse hygiene regulations to reduce cross-contamination Limit exposure to flies

The structural and parametric uncertainties resulted in five policies that were be tested. These policies were designed based on reality and are capable of providing a view of the policies' cost effectiveness and robustness.

The parametric uncertainties were used to devise a sensitivity analysis and scenario tests for robustness of the policy. The parameters are the projection of the Dutch population, the temperature increase in the coming 30 years and the cost of illness.

2.7.1 Policies tested

The policies tested on the model were implemented as described in Table 4.

Note on policy implementation

Policies were implemented using switches, connecting directly to the variable it is meant to address. This is not realistic as policies exhibit side effects. To more accurately integrate policies into the system, a group modelling approach is recommended, including relevant stakeholders such as farmers, policy experts, and public health practitioners (Vennix, 1999).

2.7.2 Scenarios tested

Policies were tested for robustness under different population, temperature change, seasonality and public health scenarios, as shown in Appendix C.3.

Specific details on the policies and on their implementations within the model can be read in Appendix C.

Table 4: Policies tested and their parameterisation

Policy Name	Description	Parameterisation
Exposure Control	Public campaigns to control human exposure to infected flies	Reduce human exposure to flies by 20% with delay of one week
Pest Control	Extermination of flies in infection prone areas	Reduce 'infectious flies variable' by 20%, triggered by temperature above 20 °
Consumption Behaviour	Public campaign encouraging population to reduce chicken meat consumption when case numbers are high	Reduce 'consumption rate per person' by 0.05 kg/week/person
Food Safety and Handling	Public campaign encouraging improved household food hygiene	Reduce infections per kg of meat consumed by 20%
Safe Slaughtering	Require slaughterhouses to implement more hygiene measures	Reduce rate of cross contamination by 20%

3 Results

In this chapter the results from the experiments are shown and analysed. First, the base model with and without scenarios is tested and discussed. Finally, the policies are implemented, and tested in combination with certain scenarios. This analysis serves an interpretation of the relative cost-effectiveness of the chosen policies, allowing for comparison of real-world cost of implementation.

3.1 Base Model

The model was run without any scenarios to generate baseline behaviour and the behaviour of KPIs examined.

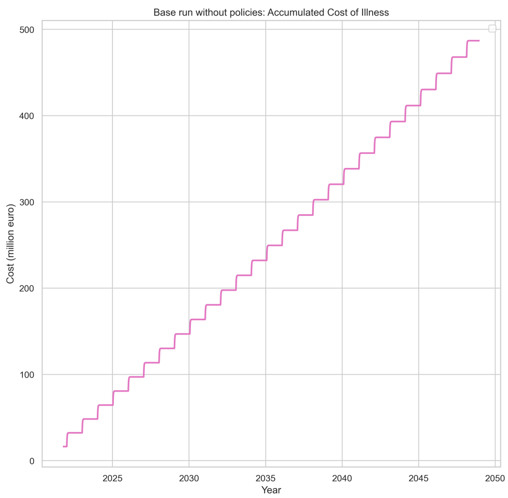

Figure 7: Cost of Illness in the base run

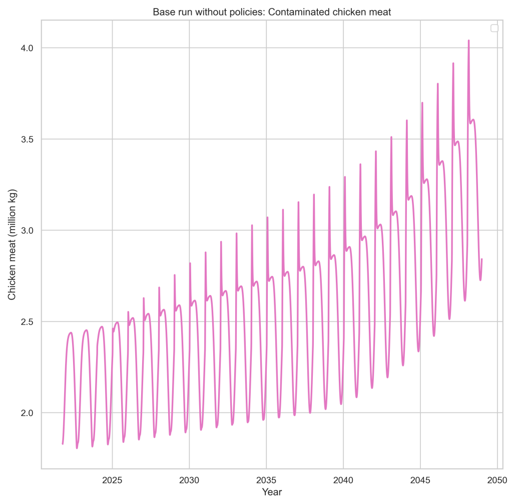

Figure 8: Contaminated chicken meat in the base run

The model generated behaviour that was generally consistent with the dynamic hypothesis, with three main exceptions:

The contaminated meat stock (Figure 8) exhibits unusual behaviour due to a structural uncertainty linking the number of *Campylobacter* cases to changes in meat consumption. After a given threshold number of cases have occurred in the population, we assume there would be a change in behaviour of people choosing to consume less chicken meat to avoid infections. This results in a temporary spike in the contaminated meat stock while the poultry industry responds to changing consumer demand. This spike is indicative of a potential economic loss to

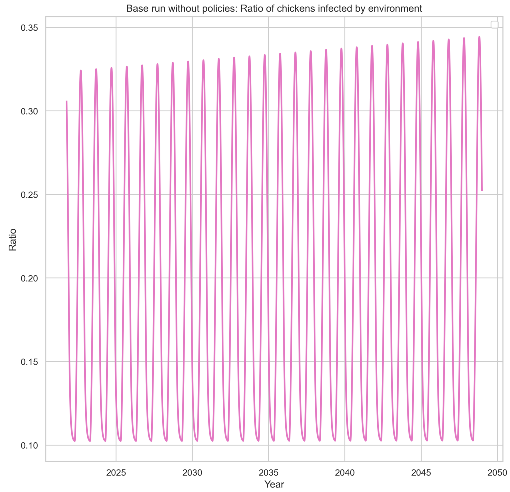

Figure 9: Chicken infections from environment in the base run

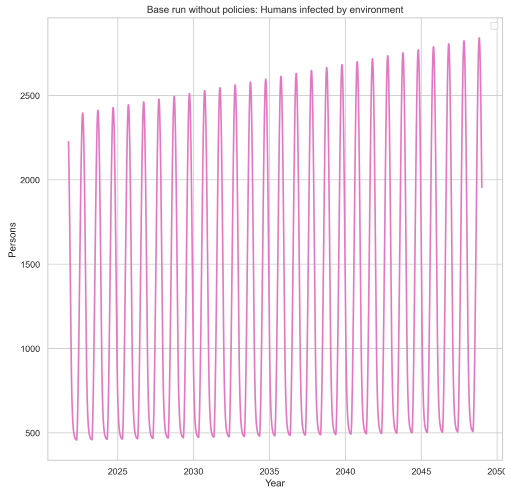

Figure 10: Human infections from environment in the base run

the poultry industry and to retailers, which is not captured in this model. This limitation is discussed in chapter 4.

Secondly, initially we did not account for seasonality in the development of the contaminated meat stock, but it ended being the case.

Finally, the model produces a stepped graph for the cost of illness, where we had hypothesised a straight line instead. This has to do with the switch in units mentioned in section 2.6.1. The increase in Cost of Illness occurs once yearly, resulting in the steps in (Figure 7). A continuous time step would have resulted in a straight line as hypothesised.

3.2 Policy Robustness

In this section, results of scenario testing of each of the policies was examined, to understand which policies were most robust and most cost effective, to inform policy recommendations.

3.2.1 Safe Slaughtering

Scenario analysis demonstrated that while safe slaughtering is relatively robust over most scenarios, it is not cost-effective. The policy addresses infection rates after some number of the flock is already infected, making it more reactive than other policies, which focus on addressing environmental effects. However, this does not seem to work as well.

Interpretation of the cost of illness across all scenarios demonstrated that only modest economic savings are achieved with this policy (in the order of €0.5 million over the entire thirty year time horizon), as seen in Figure 11. Furthermore, our model does not take costs to farmers implementing this policy into account, so the aggregate cost effect is unlikely to be positive.

Based on these results, we would not recommend prioritising the safe slaughtering policy over other policies due to its limited effectiveness. This becomes apparent in Figure 12, where it can be seen that its influence does not prevent worst case scenario from occurring.

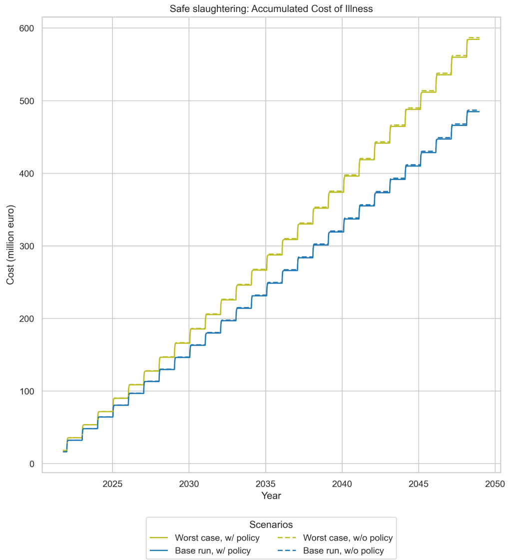

Figure 11: Accumulated cost of illness under best and worst case scenario, solid lines represent conditions with policy, dashed lines are condition without policy

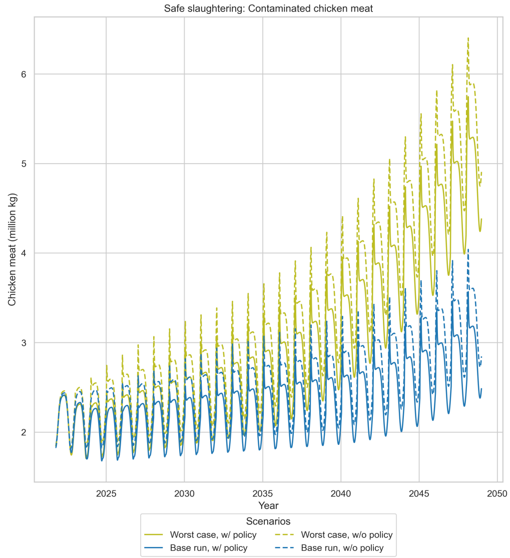

Figure 12: Contaminated chicken meat in the best and worst case scenario, solid lines represent conditions with policy, dashed lines are condition without policy

3.2.2 Pest Control

The Pest Control policy was found to be robust against climate change scenarios, with no observable difference between KPI outcomes for different climate scenarios, as can be seen in Figure 13. This is because the policy is pegged to temperature, effectively capping propagation of flies at higher temperatures. However, it is less robust to changes in seasonality, wherein after 2030, there is a divergence in outcomes. For scenarios with greater seasonality, the policy of controlling fly populations is less capable of responding to larger variation in temperature.

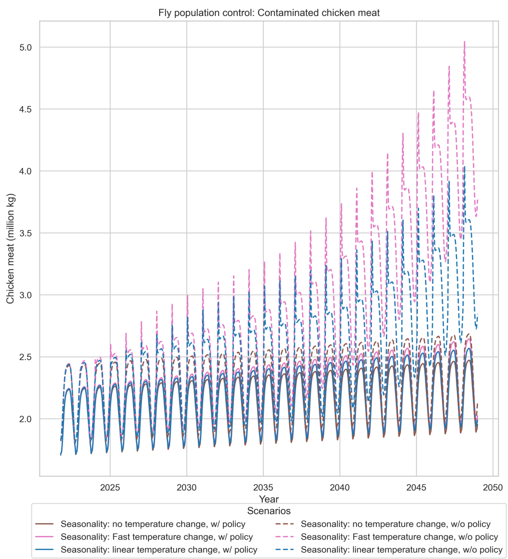

Figure 13: Contaminated chicken meat under different seasonality conditions, solid lines represent conditions with policy, dashed lines are condition without policy

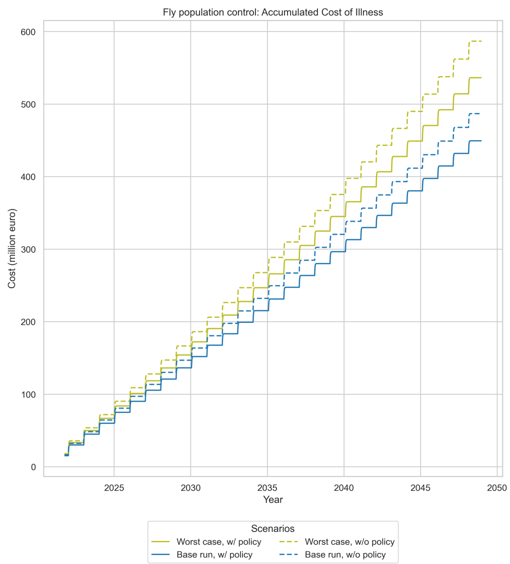

Figure 14: Accumulative cost of illness under the base and worst case scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

Predictably, the policy does not influence changes in public health scenarios, as the effects are too far downstream of the policy for pest control to have a material impact.

As pest control is robust to climate variation, we recommend that policy-makers consider this as an effective policy under futures with climate uncertainty, but should be paired with other policies to manage for downstream effects (especially with respect to public health scenarios). In the near term, this policy is unlikely to be cost-effective, however, from 2030 onward (assuming climate projections are representative), the economic effects of the policy will be large enough (more than €10 million) to justify expenditure on this policy, as shown in Figure 18.

Note: This policy is implemented without delay. It was assumed that if a policy is in place to exterminate flies once temperature exceeds 20 °Celsius, governments can trigger an immediate extermination at relevant locations.

3.2.3 Food safety and handling

The Food Safety policy is a robust policy in terms of reducing food-borne *Campylobacter* infections. This is evidenced in the Figure 15 whereby the gap between the amount of contaminated meat with and without the policy in place widens over time across all scenarios. Even under higher population estimates, this policy was effective for reducing this case load.

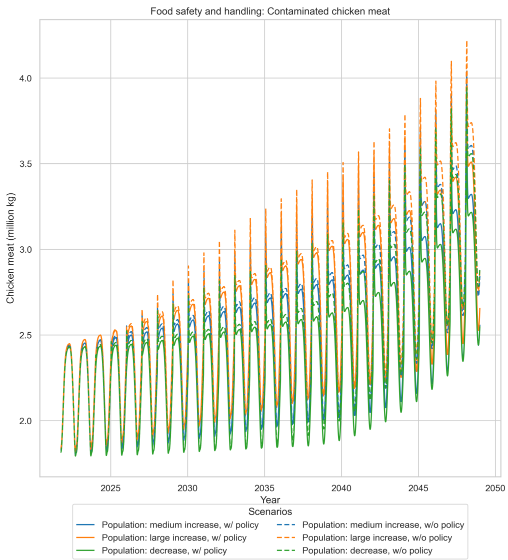

Figure 15: Contaminated chicken meat under different population scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

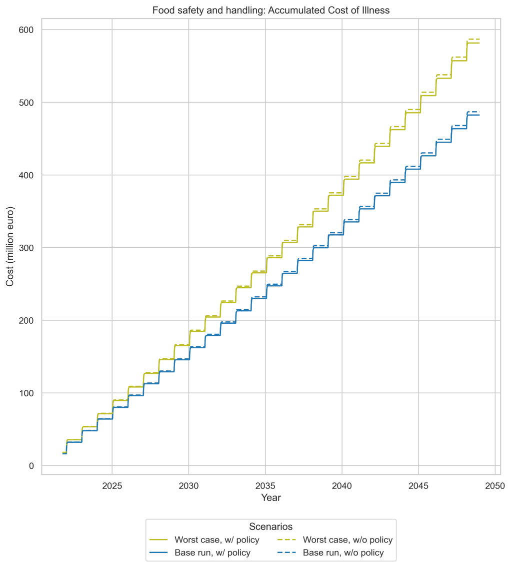

Figure 16: Accumulative cost of illness under the base and worst case scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

However, this policy was considerably less effective and robust against environmental transmissions, where the policy has little to no effects under all scenarios. This policy exhibits only a modest cost effectiveness, as shown in Figure 16.

3.2.4 Poultry consumption behaviour

This policy only activated under the worst case scenario. Essentially, this policy represents a last resort for the government. It is safe to assume that the government will not enact this policy except for under extenuating circumstances, whereby case numbers get so high that all other policy options are exhausted, and the government needs to ask citizens to reduce poultry consumption.

What we see is that when the policy was enacted, the amount of contaminated chicken meat decreases drastically. After some time, it even shows behaviour that is more desirable than without the policy enacted. However, the financial benefits of the policy are not significant for quite a while, as seen in Figure 18.

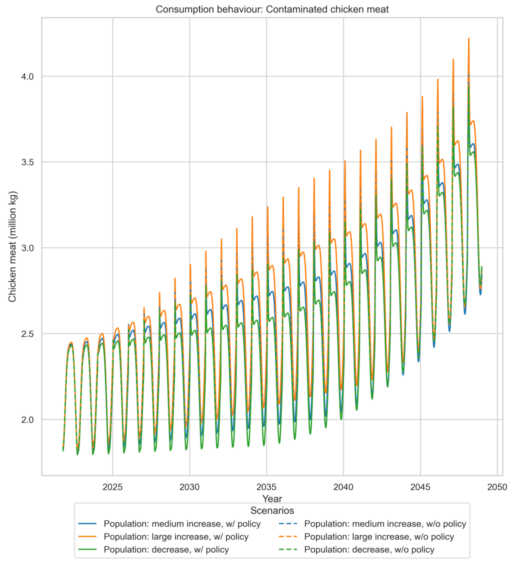

Figure 17: Contaminated chicken meat under different population scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

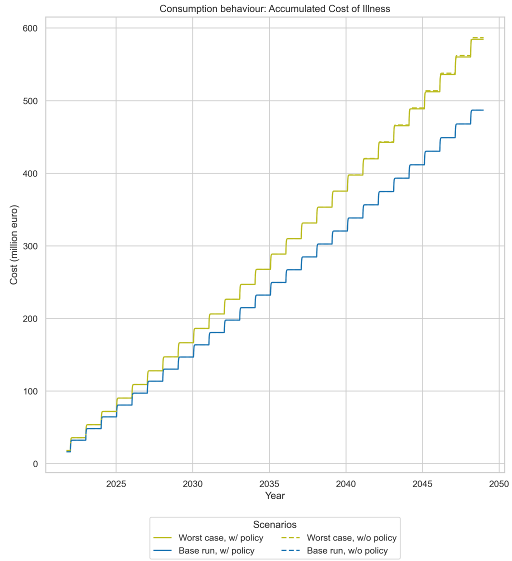

Figure 18: Accumulative cost of illness under the base and worst case scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

It is worth noting that this policy had an overlap with the consumption behaviour that is already embedded in the model. People might reduce their consumption on their own regardless of what the government recommends, further reducing the value gained from this policy.

3.2.5 Reducing human exposure to flies

Reducing human exposure to flies was found to be the most robust of all the policies examined. It is also the second most cost-effective of the policies examined, in terms of reducing cost of illness. This is evident in 20. This policy is effective for reducing the human-related KPIs (Cost of Illness, DALYs, Human Environmental Infections) across all scenarios.

It is believed that this policy is effective as it is a quick and direct means of reducing environmental infection, which subsequently reduces downstream KPIs. It does not require change in inelastic behaviour and does not replicate an existing behavioural uncertainty (like for changing consumption behaviour) so effects on infections can be observed relatively rapidly.

Given the cost-effectiveness and robustness of this policy, we would recommend that this policy to be considered by the Dutch government and to be further investigated (for instance, by incorporating additional environmental transmission pathways). This may ultimately reduce the policy's estimates of effectiveness, but would provide more realistic insight for decision-makers.

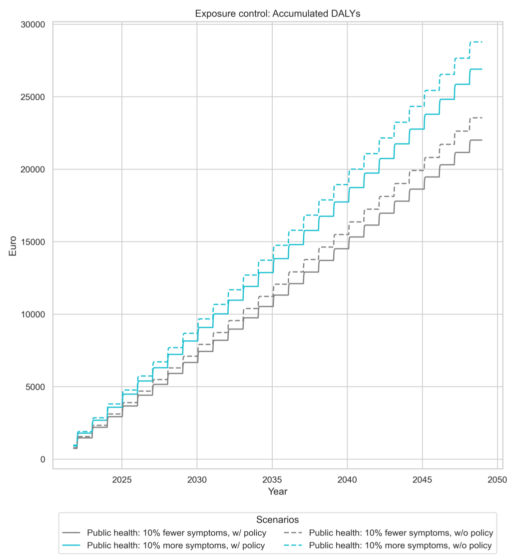

Figure 19: Accumulated DALYs under different public health scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

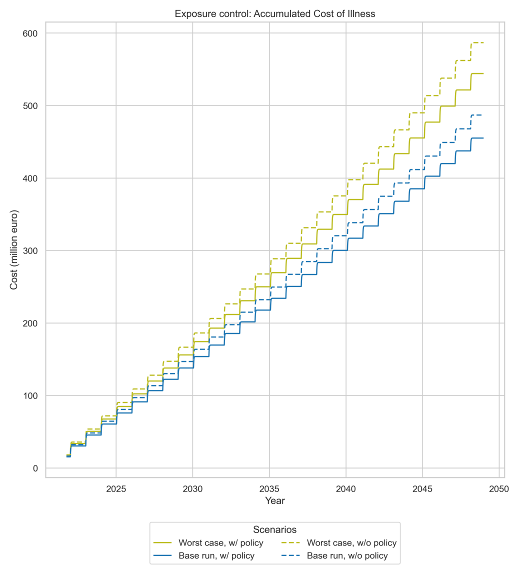

Figure 20: Accumulative cost of illness under the base and worst case scenarios, solid lines represent conditions with policy, dashed lines are condition without policy

4 Conclusion and Recommendations

In this section we answer the research question and tie all individual finding together. The results from section 3 are related to the research question, after which the implications and limitations are discussed. Suggestions for further research are also included.

4.1 Key Findings

The model was built and analysed with the following research question in mind:

What are the economic impacts of Campylobacter under different climate, population, and public health scenarios, and what policy measures can address these?

Through the results, we were able to examine the economic impacts of *Campylobacter* infections, using Cost of Illness as a measure of this impact. Modelling of the system for changing population, public health circumstances, and climate found the cumulative impacts by the year 2050 given in Table 5

Table 5: Accumulated Cost of Illness by 2050 under main scenarios

Model Scenario	Economic Impact
Base	€486.9 million
Climate - 2 °warming	€493.8 million
Seasonality - warmer summers	€495.8 million
Population - maximum projection	€514.8 million
Public health - increased symptomatic	€535.6 million

The model also generated information on the DALY (public health) impact of *Campylobacter* under different scenarios. This information can be helpful to those in the public health field to compare the effectiveness of different interventions in a relevant public health metric.

4.2 Policy Recommendations

From this analysis, we recommend the following combination of policies to ensure a policy mix both cost-effective (measured by the ability to reduce cost of illness) and robust to a range of climate, population, and public health scenarios:

- Exposure control: We recommend that the Dutch Government investigate an exposure control policy as specified to reduce environmental infection routes for human *Campylobacter* infections. This approach does have limitations, but was found to be the most effective of the policies implemented in the system dynamics model in reducing human infections.
- Pest control: We recommend that the Dutch Government also investigate pest control/targeted extermination campaigns to control fly populations in locations where they are likely to spread *Campylobacter*, as this was found to be the most effective policy for reducing environmental chicken infections.
- Consumption behaviour (retained as a policy of last resort): We recommend that the Dutch Government formulate a consumption behaviour policy for deployment as a 'policy of last resort' to reduce infections in the short term in response to individual outbreaks of *Campylobacter*. This policy was found to be robust, but only really effective as a policy under extreme circumstances.

Policies for implementation by other stakeholders were not considered through this work.

4.3 Limitations and Future Work

Developing the model, components were approximated or simplified to ensure the model was comprehensible and development time reasonable. These choices present limitations to the model and are documented here, along with recommendations for future work to address them.

Ultimately, the most significant limitation of the work is that of the subjective view of the modellers. Conceptualisation, formalisation, validation and analysis are all subject to the biases and mental models of the group responsible for building the model, so the model will benefit from external assessment and validation.

4.3.1 Limitations of Conceptualisation

Conceptualisation limitations arise mainly through the abstraction of certain parts and consciously excluded factors.

The environmental submodel does not include waterborne infection pathways for either chickens or humans. This is due to a lack of literature and difficulty in representing these pathways when considering poultry farming in the Netherlands as one homogeneous unit. Future work should investigate waterborne pathways for infection.

Precipitation changes were excluded from the modelling of climate and environmental effects during the conceptualisation of the model, as the disease vectors and transmission pathways examined were not significantly influenced by rainfall. Furthermore, the model excludes impacts on health system capacity from the model (i.e. modelling numbers of patients visiting doctors, hospitals, intensive care). Future work should include rainfall in the climate effects and environmental transmission sub-model and expand the cost of illness and health impacts to include health system capacity in measures of public health impact.

4.3.2 Limitations of Formalisation

Formalisation of the model resulted in some changes and simplifications in order to simulate. The stability of the model behaviour suggests that some elements may have been oversimplified. This can be addressed through consultation with relevant stakeholders about realistic behaviours.

The temperature in the climate model was implemented as a perfect sinusoidal curve. In reality, seasonal fluctuations exhibit more randomness, with intermittent peaks and troughs. Future work should integrate existing validated climate models for more realistic variability.

Due to the focus on the COI, illness and recovery dynamics were not fully modelled. There is no recovered population stock which would, within a Susceptible-Infected-Recovered (SIR) model, typically result in members of the population developing immunity to *Campylobacter*, preventing reinfection. Future work should include a SIR structure to prevent possible double-counting of infected persons.

Furthermore, there are no population cohorts used in examining public health impacts. This was because the DALY and COI figures used already account for impacts across different age groups. Future work might consider subscripting the model to explicitly model sub-components of DALYs for different population compositions to understand implications of ageing and other population dynamics.

The model assumes supply for chicken meat is strongly coupled to demand, lending stability to the model that may not be representative of reality. Future modelling efforts should include means to better reflect the elasticity of demand and supply to policy changes.

In the modelled system, the environmental submodel was structured such that flies still thrive under extreme heat conditions. Future modelling of this system should include ceilings on the effect linking temperature to fly population.

4.3.3 Limitations of Validation

Limitations on validation relate to the possible ranges of values that variables can take. Surrounding temperature and population increase over time, there is significant uncertainty. And with others, like the initial fly population, there is no data to compare directly with. Similarly, in extreme conditions testing it is challenging to assess precise boundaries for model validity, since it is difficult to define, for example, how many flies are too many.

Uncertainty in the validation of consumption behaviour and related policies might be reduced by conducting household behavioural surveys before and after *Campylobacter* infection. Other elements of the model can be further improved by employing group model building as discussed in section 2.4, which could reduce uncertainty by capturing tacit knowledge regarding policy measures' effectiveness and other structural uncertainties.

A group model building approach might also highlight opportunities for new research on the environmental transmission of *Campylobacter*. We found literature was scarce on fly transmission routes through the modelling process, including on how flies infect one another, how they infect other animals, and how other disease vectors (such as wild birds) are involved. Involving subject matter experts in the modelling process might help close this gap.

4.3.4 Limitations of Analysis

Group model building would also benefit the quality of analysis. In analysing the policies and the model, the range of scenarios tested were limited to the available information. A consultative approach could enable the modellers to adopt a broader set of feasible external factors (based on expert input) against which to test the efficacy and robustness.

The cost of illness was taken as the leading indicator for economic impact. This captures the economic effects of public health impacts, but not the direct economic effects related to changes in farm management practices. Future work should integrate knowledge from farmers and the agricultural industry on the direct costs of implementing policies such as safe slaughtering or costs incurred by businesses resulting from depressed poultry consumption.

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A Model documentation

Variable name	Type	Units	Initial value	Equation	Source	Important assumptions	Submodel
chickens arriving from hatcheries	Flow	Chicken/Week	na	population*(consumption rate per person/meat per chicken)	Model conceptualization	Supply = Demand	Chicken
chicken on farms	Stock	Chicken	Initial Chickens on Farms	chickens arriving from hatcheries-chicken infections with CPY-"chicken non-infections with CPY"	Model conceptualization		Chicken
initial chickens on farms	Constant	Chicken	na	100000	Model conceptualization	Arbitrary number	Chicken
CPY-positive chickens	Stock	Chicken	0	chicken infections with CPY-"CPY-positive chickens slaughtered"	Model conceptualization		Chicken
chicken infections with CPY	Flow	Chicken/Week	na	chickens on farms*rate of chicken infection from environment	Model conceptualization		Chicken
chicken non-infections with CPY	Flow	Chicken/Week	na	chickens on farms*(1-rate of chicken infection from environment)	Model conceptualization		Chicken
CPY-negative chickens	Stock	Chicken	0	chicken non-infections with CPY-"slaughtering with cross-contamination"-"slaughtering without cross-contamination"	Model conceptualization	This is the final contamination before slaughtering	Chicken
slaughtering without cross-contamination	Flow	Chicken/Week	na	CPY-negative chickens * (1-"rate of cross-contamination")	Model conceptualization		Chicken
slaughtering with cross-contamination	Flow	Chicken/Week	na	CPY-negative chickens * "rate of cross-contamination"	Model conceptualization		Chicken
contaminated meat	Stock	kg	0	("CPY-positive chickens slaughtered"+"slaughtering with cross-contamination")*meat per chicken-contaminated meat consumption	Model conceptualization	This stock includes a modifier to change from chickens to chicken meat (changes units from chicken to kg). This is outside of convention, but was a necessary modifier to make the stock-flow structure work.	Chicken
CPY-positive chickens slaughtered	Flow	Chicken/Week	na	CPY-positive chickens*slaughter rate	Model conceptualization	All infected chicken become contaminated meat	Chicken
rate of cross-contamination	Variable	1/Week	na	IF THEN ELSE(safe slaughtering policy = 1, ((ZIDZ("CPY-positive chickens",("CPY-negative chickens"+"CPYpositive chickens")))*CPY reproduction in chickens)*0.8 , (ZIDZ("CPY-positive chickens",("CPY-negative chickens"+"CPY-positive chickens")))*CPY reproductive number in chickens)	Model conceptualization	Depends on the proportion of infected chicken	Chicken
meat per chicken	Constant	Kg/Chicken	na	1,5	Denton & Miller, 1988; National Chicken Council 2021		Chicken
contaminated meat consumption	Flow	Kg/Week	na	MIN(proportion of contaminated meat * consumption rate per person * population, (contaminated meat/week))	Model conceptualization	Cannot consume more than there is available	Chicken
total chickens slaughtered	Variable	Chicken/Week	na	CPY-positive chickens slaughtered+"slaughtering with cross-contamination"+"slaughtering without cross-contamination"	Model conceptualization		Chicken
contaminated slaughtered chickens	Variable	Chicken/Week	na	CPY-positive chickens slaughtered+"slaughtering with cross-contamination"	Model conceptualization		Chicken
Proportion of contaminated meat	Variable	Dmnl	na	ZIDZ(contaminated slaughtered chickens,total chickens slaughtered)	Model conceptualization		Chicken
slaughter rate	Constant	1/Week	na	0,3	Calibration	30% of all chickens present on the farms are slaughtered each week	Chicken
proportion of CPY-positive chickens	Variable	Dmnl	na	ZIDZ("CPY-positive chickens", "CPY-positive chickens"+"CPY-negative chickens")	Model conceptualization		Chicken
consumption rate per person	Constant	kg/(Week*Person)	na	0.203+meat consumption behaviour	https://files.wakkerdier.nl/app/uploads/2020/10/20151422/2020-078-Vleesconsumptie-2019-WUR-Dagevos_def.pdf?_ga=2.115483654.1629359199.1615461809-1770319697.1615461809		Chicken
population	Variable	Person	na	population by 2020 + RAMP((projected population by 2050-population by 2020)/(weeks per year*30),0,weeks per year*30)	Model conceptualization		Chicken
week	Constant	Week	na	1			Chicken
CPY reproduction in chickens	Constant	1/Week	na	0,5	(Campylobactor) in a Dairy herd. In 19th International		Chicken
Infections per kg of meat consumed	Variable	Cases/kg	na	IF THEN ELSE(food safety policy=1, 0.8*5e-05, 5e-05)	Calibration		Cost of Illness
CPY Cases	Stock	Cases	0	human CPY infections-asymptomatic infections-symptomatic infections	Model conceptualization		Cost of Illness
human CPY infections	Flow	Cases/Week	na	(contaminated meat consumption*infections per kg of meat consumed)+rate of human infection from environment	Model conceptualization		Cost of Illness
Acute GE Cases	Stock	Cases	0	symptomatic infections-Death by CPY-GBS development-GE Recovery-IBD development-ReA development	Model conceptualization		Cost of Illness

symptomatic infections	Flow	Cases/Week	na	(CPY Cases*rate of symptomatic cases)*(PULSE TRAIN(weeks per year, TIME STEP, weeks per year , FINAL TIME)) / TIME STEP	Model conceptualization		Cost of Illness
base rate of symptomatic cases	Constant	Dmnl	na	0,88	Medema et al.		Cost of Illness
rate of symptomatic cases	Variable	Dmnl	na	base rate of symptomatic cases*rate of symptomatic cases modifier	Model conceptualization		Cost of Illness
asymptomatic infections	Flow	Cases/Week	na	(CPY Cases*(1-rate of symptomatic cases))*(PULSE TRAIN(weeks per year, TIME STEP, weeks per year , FINAL TIME)) / TIME STEP	Model conceptualization		Cost of Illness
GE Recovery	Flow	Cases/Week	na	recovery rate*Acute GE Cases	Model conceptualization		Cost of Illness
recovery rate	Constant	1/Week	na	0,98125	Mangen et al.		Cost of Illness
ReA Cases	Stock	Cases	0	ReA development	Model conceptualization	Chronic disease, does not empty	Cost of Illness
GBS Cases	Stock	Cases	0	GBS development	Model conceptualization	Chronic disease, does not empty	Cost of Illness
IBD Cases	Stock	Cases	0	IBD development	Model conceptualization	Chronic disease, does not empty	Cost of Illness
Death by CPY	Flow	Cases/Week	na	Acute GE Cases*death rate	Model conceptualization	Disease burden/cost of illness associated with deaths accounted for within DALY metric. This flow is only used to empty the cases stock	Cost of Illness
ReA development	Flow	Cases/Week	na	Acute GE Cases*ReA rate	Model conceptualization	Development of chronic disease assumed to all occur subsequent to acute cases. In reality, some campylobacter infections do connect directly to incidence of chronic disease.	Cost of Illness
GBS development	Flow	Cases/Week	na	Acute GE Cases*GBS rate	Model conceptualization		Cost of Illness
IBD development	Flow	Cases/Week	na	Acute GE Cases*IBD rate	Mangen et al.		Cost of Illness
ReA rate	Constant	1/Week	na	0,0175	Mangen et al.		Cost of Illness
GBS rate	Constant	1/Week	na	0,00075	Mangen et al.		Cost of Illness
IBD rate	Constant	1/Week	na	0,000125	Mangen et al.	Rate doubled to account for increase in diagnosis of IBD over past 2 decades: https://www.cdc.gov/ibd/data-statistics.htm#:~:text=Inflammatory%20Bowel%20Disease%20Prevalence%20(IBD,%25%20or%202%20million%20adults).	Cost of Illness
death rate	Constant	1/Week	na	0,000375	Mangen et al.	Assumed that death only caused by acute symptoms, death from chronic cases largely contained within DALYs.	Cost of Illness
DALY	Variable	DALY	na	(recovered GE*DALYs per GE Case) + (GBS Cases*DALYs per GBS Case) + (IBD Cases*DALYs per IBD Case) + (ReA Cases*DALYs per ReA Case)	Model conceptualization		Cost of Illness
Cost of Illness	Variable	Euro	na	((recovered GE*COI per GE Case) + (GBS Cases*COI per GBS Case) + (IBD Cases*COI per IBD Case) + (ReA Cases*COI per ReA Case))*COI modifier	Model conceptualization		Cost of Illness
COI modifier	Constant	Dmnl	na	1	Model conceptualization	Used only to test sensitivity	Cost of Illness
DALYs per GE Case	Constant	DALY/Cases	na	0,008	Mangen et al.	All undiscounted DALYs	Cost of Illness
DALYs per ReA Case	Constant	DALY/Cases	na	0,09	Mangen et al.	All undiscounted DALYs	Cost of Illness
DALYs per GBS Case	Constant	DALY/Cases	na	5	Mangen et al.	All undiscounted DALYs	Cost of Illness
DALYs per IBD Case	Constant	DALY/Cases	na	11,6	Mangen et al.	All undiscounted DALYs	Cost of Illness
COI per GE Case	Constant	Euro/Cases	na	190	Mangen et al.		Cost of Illness
COI per ReA Case	Constant	Euro/Cases	na	20	Mangen et al.		Cost of Illness
COI per GBS Case	Constant	Euro/Cases	na	85000	Mangen et al.		Cost of Illness
COI per IBD Case	Constant	Euro/Cases	na	173000	Mangen et al.		Cost of Illness
Recovered GE	Stock	Cases	0	GE Recovery	Model conceptualization		Cost of Illness
weeks per year	Constant	Week	na	52	This is how time works.		Cost of Illness
consumer food consumption behaviour lever	Variable	Dmnl	na	IF THEN ELSE((known CPY cases/population) > consumer food consumption behaviour threshold , 1 , 0)	Model conceptualization	0 - Normal consumption 1 - Reduced consumption due to too many cases	Cost of Illness
consumer food consumption behaviour threshold	Constant	Cases/Person	na	0,0038	Own interpretation		Cost of Illness
time to know about CPY cases	Constant	Week	na	1	Own interpretation		Cost of Illness
known CPY cases	Variable	Cases	na	SMOOTH N(CPY Cases,time to know about CPY cases, CPY Cases, 3)	Model conceptualization		Cost of Illness
meat consumption behaviour	Variable	kg/(Week*Person)	na	IF THEN ELSE(((consumer food consumption behaviour lever + consumption behaviour policy) = 0), 0 , -0.05)	Model conceptualization	Natural consumer behavior and government intervention to modify behavior do not compound	Cost of Illness

rate of symptomatic cases modifier	Variable	Dmnl	na	WITH LOOKUP (scenario switch): ([(0,0)-(12,2)],(0,1),(9,1),(10,0.9),(11,1.1),(12,1.1))	Mangen et al.	Ranges from 0.9 to 1.1 across scenarios	Cost of Illness
fly population	Stock	MFly	initial fly population	fly development-fly deaths	Model conceptualization		Environmental
fly deaths	Flow	MFly/Week	na	DELAY1I(fly development, fly lifetime, fly population/fly lifetime)	Model conceptualization		Environmental
fly development	Flow	MFly/Week	na	fly development rate	Model conceptualization		Environmental
Initial fly population	Constant	MFly	na	0,1	Model conceptualization		Environmental
fly lifetime	Constant	Week	na	4	https://www.orkin.com/flies/how-long-do-flies-live		Environmental
fly population growth per degree	Constant	MFly/(degree*Week)	na	0,0024	Blanckenhorn, W. U. (1997). Effects of temperature on growth, development and diapause in the yellow dung fly - against all the rules? Oecologia, 111(3), 318–324. doi:10.1007/s004420050241		Environmental
base fly population development rate	Constant	MFly/Week	na	-0,0091	Blanckenhorn, W. U. (1997). Effects of temperature on growth, development and diapause in the yellow dung fly - against all the rules? Oecologia, 111(3), 318–324. doi:10.1007/s004420050241		Environmental
non-diapause development rate	Variable	MFly/Week	na	base fly population development rate + fly population growth per degree* temperature	Blanckenhorn, W. U. (1997). Effects of temperature on growth, development and diapause in the yellow dung fly - against all the rules? Oecologia, 111(3), 318–324. doi:10.1007/s004420050241		Environmental
diapause development rate	Constant	MFly/Week	na	0,0005	Blanckenhorn, W. U. (1997). Effects of temperature on growth, development and diapause in the yellow dung fly - against all the rules? Oecologia, 111(3), 318–324. doi:10.1007/s004420050241		Environmental
fly development rate	Variable	MFly/Week	na	IF THEN ELSE(temperature > 4, "non-diapause development rate" ,diapause development rate)	Blanckenhorn, W. U. (1997). Effects of temperature on growth, development and diapause in the yellow dung fly - against all the rules? Oecologia, 111(3), 318–324. doi:10.1007/s004420050241	Below 4 degrees fly development enters diapause	Environmental
temperature	Variable	degree	na	((-1)*(SIN(2*pi*(Time+start of year offset)/weeks per year))*((maximum average weekly temperature-minimum average weekly temperature)/2)+((maximum average weekly temperature+minimum average weekly temperature)/2))+temperature increase	Model conceptualization	More than four inputs to the variable - this presents issues for readability, but all variables were necessary for formulation.	Environmental
minimum average weekly temperature	Variable	degree	na	-4	KNMI		Environmental
maximum average weekly temperature	Variable	degree	na	23	KNMI		Environmental
pi	Constant	Dmnl	na	ARCCOS(-1)	Archimedes of Syracuse		Environmental
proportion of infectious flies	Variable	Dmnl	na	base infectious flies + "chance of chicken-to-fly transmission"* "proportion of CPY-positive chickens"	Model conceptualization		Environmental
chance of chicken-to-fly transmission	Constant	Dmnl	na	0,5	Calibration		Environmental
base infectious flies	Constant	Dmnl	na	0,35	Calibration		Environmental
infectious flies	Variable	MFly	na	fly population*proportion of infectious flies * IF THEN ELSE(fly population control policy = 1 ,0.8 ,1)	Model conceptualization		Environmental
rate of chicken infection from environment	Variable	1/Week	na	base chicken exposure rate+(infectious flies*rate of chicken exposure to infectious flies)	Model conceptualization		Environmental
human infection from environment	Variable	Cases/Week	na	infectious flies*rate of human exposure to infectious flies*population + (infection risk from birds * population)	Model conceptualization		Environmental
base chicken exposure rate	Constant	1/Week	na	0,1	Calibration		Environmental
chicken exposure to infectious flies	Variable	1/(MFly*Week)	na	2	Calibration		Environmental
rate of human exposure to infectious flies	Variable	Cases/(MFly*Person*Week)	na	base human exposure rate * SMOOTH(IF THEN ELSE(exposure control policy = 1 , 0.8 , 1) , number of weeks needed to adopt policy)	Model conceptualization		Environmental

base human exposure rate	Constant	Cases/(MFly*Week*Person)	na	0.001	Calibration		Environmental
average temperature increase	Variable	degree	na	RAMP(temperature increase by 2050/(weeks per year*30),0,weeks per year*30)	Model conceptualization		Environmental
temperature switch	Variable	Dmnl	na	WITH LOOKUP (scenario switch):([(0,0)-(12,2)],(0,0),(7,0),(8,2),(9,1),(10,0),(11,0),(12,2))	Model conceptualization	0 - No change 1 - Linear change 2 - Faster summer warming than winter warming	Environmental
temperature increase	Variable	degree	na	IF THEN ELSE(temperature switch = 0,0,(IF THEN ELSE(temperature switch = 2,(-1)*(SIN(2*pi*(Time+start of year offset)/weeks per year)*0.8*average temperature increase)+average temperature increase,average temperature increase)))	Bresser et al, 2006		Environmental
temperature increase by 2050	Constant	degree	na	WITH LOOKUP (scenario switch): ([(0,0)-(12,2)],(0,1.5),(3,1.5),(4,1),(5,1.5),(6,1.5),(7,1.5),(8,2),(9,1.5),(11,1.5),(12,2))	KNMI 14' klimaatscenario's voor Nederland	Ranges from 1 to 2 across the different scenarios	Environmental
Infection risk from birds	Constant	Cases/(Week*Person)	na	2,5E-0,5	Calibration		Environmental
start of year offset	Variable	Week	na	8	KNMI	Needed to make the sinusoidal curve for the temperature to match the appropriate time of year.	Environmental
population by 2020	Constant	Person	na	1,73E+07	CBS		Environmental
projected population by 2050	Variable	Person	na	WITH LOOKUP (scenario switch): ([(0,0)-(12,3e+07)],(0,1.94e+07),(1,1.94e+07),(2,2.16e+07),(3,1.71e+07),(4,1.94e+07),(11,1.94e+07),(12,2.16e+07))	CBS (https://www.cbs.nl/en-gb/news/2020/51/forecast-population-growth-unabated-in-the-next-50-years)	Ranges from 1.71e+07 to 2.16e+07 across scenarios	Environmental
exposure control policy	Variable	Dmnl	na	IF THEN ELSE(exposure control policy switch = 1, IF THEN ELSE(temperature > temperature trigger for exposure control policy, 1 , 0), 0)	Policy conceptualization		Policies
temperature trigger for exposure control policy	Constant	degree	na	20	Policy conceptualization		Policies
exposure control policy switch	Constant	Dmnl	na	0	Policy conceptualization	0 - No policy 1 - Policy implemented	Policies
number of weeks needed to adopt policy	Constant	Week	na	2	Policy conceptualization		Policies
fly population control policy	Variable	Dmnl	na	IF THEN ELSE(fly population control policy switch = 1, IF THEN ELSE(temperature > temperature trigger for fly population control policy , 1 , 0), 0)	Policy conceptualization		Policies
temperature trigger for fly population control policy	Constant	degree	na	20	Policy conceptualization		Policies
fly population control policy switch	Constant	Dmnl	na	0	Policy conceptualization	0 - No policy 1 - Policy implemented	Policies
safe slaughtering policy	Variable	Dmnl	na	IF THEN ELSE(safe slaughtering policy switch = 1, IF THEN ELSE(Cost of Illness-COI accumulated a year ago > COI trigger for slaughtering policy , 1 , 0), 0)	Policy conceptualization		Policies
COI trigger for slaughtering policy	Constant	Euro	na	1,50E+07	Policy conceptualization		Policies
safe slaughtering policy switch	Constant	Dmnl	na	0	Policy conceptualization	0 - No policy 1 - Policy implemented	Policies
consumption behaviour policy	Variable	Dmnl	na	IF THEN ELSE(consumption behaviour policy switch = 0, 0 , IF THEN ELSE ((Cost of Illness-COI accumulated a year ago)<COI trigger for consumption behaviour policy,0, (PULSE(weeks per year,1500)*1)))	Policy conceptualization		Policies
COI accumulated a year ago	Level	Euro	na	DELAY FIXED (Cost of Illness, weeks per year,0)	Policy conceptualization		Policies
COI trigger for consumption behaviour policy	Constant	Euro	na	2,20E+07	Policy conceptualization		Policies
consumption behaviour policy switch	Constant	Dmnl	na	0	Policy conceptualization	0 - No policy 1 - Policy implemented	Policies
food safety policy	Variable	Dmnl	na	IF THEN ELSE(food safety policy switch = 1, IF THEN ELSE(Cost of Illness-COI accumulated a year ago > COI trigger for food safety policy , 1 , 0), 0)	Policy conceptualization		Policies
COI trigger for food safety policy	Constant	Euro	na	1,50E+07	Policy conceptualization		Policies
food safety policy switch	Constant	Dmnl	na	0	Policy conceptualization	0 - No policy 1 - Policy implemented	Policies

B Validation

In order to build confidence in our system dynamics model and ascertain whether our model is fit for purpose, we conducted tests on model structure and behaviour. These tests are in accordance with Forrester and Senge, 1980. Their outputs are shown in this chapter. First, we present the boundaries of the model. Second, we present our findings on the extreme conditions test. Next, we show the results of the sensitivity analysis, and we conclude this chapter by comparing the data of the model to real-world values.

B.1 Model Boundaries

A number of variables were considered in conceptualisation of the model, with most excluded from the specification. Explicit definition of variables considered in and out of scope are shown in Figure 21.

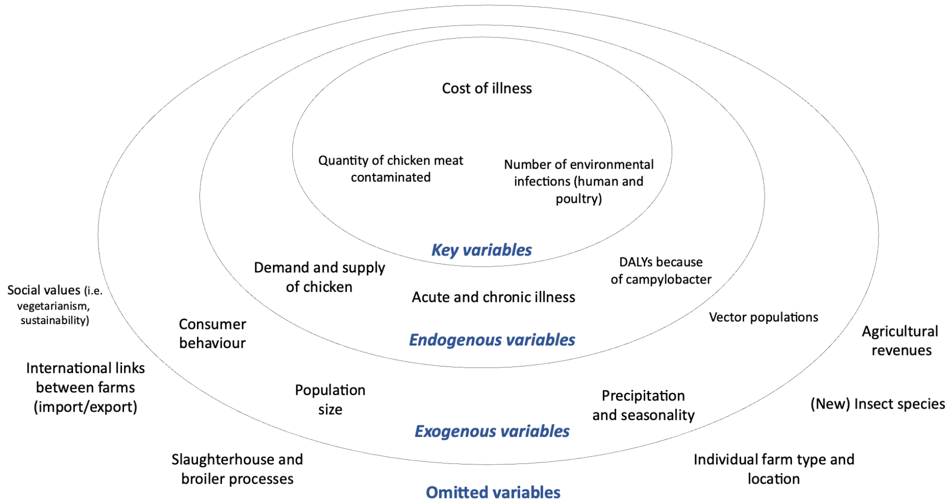

Figure 21: Bullseye diagram for variables considered within model boundaries

We included all relevant structures to address the research question. Some structures were left out because they did not fit the aggregation level.

B.2 Extreme conditions test

To test the structure of the model, we subjected it to extreme conditions to evaluate if the model behaves accordingly. Figures 22 to 28 show the results. The time horizon of these graphs is slightly bigger from the graphs used to show the results. We opted to also show the year the model takes to reach an equilibrium, which results in some interesting behaviour. In other words, we get to see the behaviour of the model in 2020.

As can be seen in Figure 22, the fly population becomes unrealistically high when the temperature gets extremely high. For instance, if throughout the year the Netherlands would have a temperature of 100 °c, we would have around 500 times more flies in the Netherlands in summer than in the baseline scenario. This is very unrealistic, as in the real world, those flies would die of the extreme heat. In the graph we show the results when *the temperature increase by 2050* is set to 25 opposed to the 1.5 °c of the baseline scenario. The flies are completely unaffected by the harsher environment.

In Figure 23, we show what happens to the KPI *proportion of contaminated meat* once the initial fly population is 0 flies and 1 million flies (1 Mfly). As can be seen, when the population is 0, relatively little meat becomes infected by the environment. However, when it is set to 1 million, we see unusual behaviour before the model reaches homeostasis in 2021. This is impossible behaviour, as a proportion should never be able to become negative or exceed 1.

This is because the amount of infectious flies is so big as a result of this initial value, the rate of chicken infection from environment becomes 2.8. In hindsight, the formula should have included a maximum. The vertex of *proportion of contaminated meat* is explained by the fact that there is more demand for chicken meat than is actually available in the stock, therefore both the *contaminated slaughtered chickens* and the*total chickens slaughtered*, which are used to calculate the ratio, are negative. Once equilibrium is reached, the behaviour of the model becomes the same as the behaviour of the baseline: around 50% of the meats are contaminated in summer, and around 23% in winter. This is a testament why the first year is out of the time horizon of our research, as it is inaccurate. After this first year the model is still valuable to analyse.

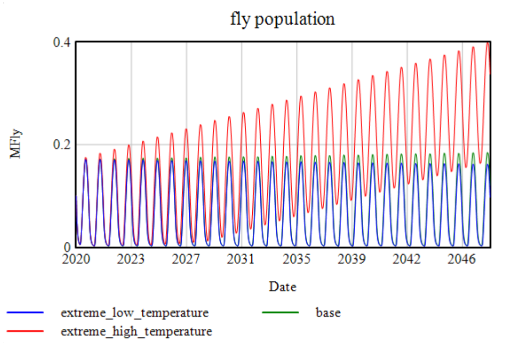

Figure 22: Effect of extreme temperature increase values on fly population

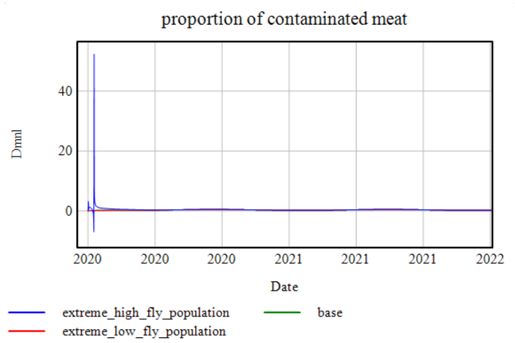

Figure 23: Effect of extreme initial fly population values on proportion of contaminated meat

We also subjected extremes on the flow *chickens arriving from hatcheries*. The results are shown in Figure 24. As to be expected, when doubled, the amount of contaminated meat grows massively, this does not propagate to the *Cost of Illness*, as the meats are just stored and the demand has not increased. The meats are just stored (in the model they are just waiting in the stock), whereas halving it actually does decrease the *Cost of Illness*, since the model recognises that the population cannot consume more chicken meat than available, and therefore there is a decreased risk of human infection via food.

Next, we investigated the *infections per kg of meat consumed*. When the value from the baseline run is halved, we do not see a significance difference in the amount of CPY cases: a decrease of around 3%, whereas when we multiply this value by twenty, the amount of CPY cases increase with around 170%. This is more than reasonably can get infected. The model does not account for people who have become immune to Campylobacter, and therefore the entire population is always at risk of becoming infected. This can be seen in Figure 25

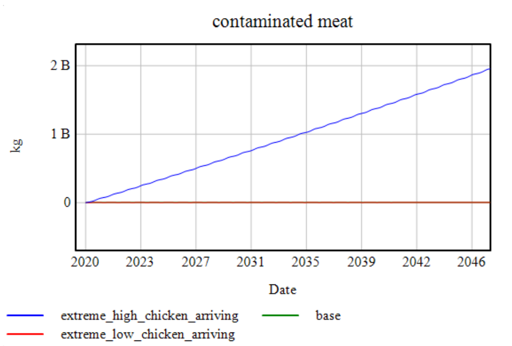

Figure 24: Effect of extreme chicken arriving to hatcheries values on contaminated meat

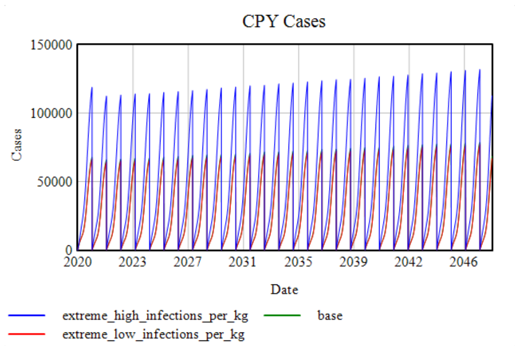

Figure 25: Effect of extreme values of infections per kg of meat consumed on Campylobacteriosis cases

We also took a closer look at the effect of *Base infected flies* on *proportion of infectious flies*. As shown in Figure 26, we found that by setting this value to the extreme 0, the proportion becomes really low. The only way for flies to get infected in the model is by getting infected by the chickens on the farms. By setting Base infected flies to 0.8, the proportion of infectious flies variable becomes an impossible ratio (over 1). This is due to the formula used to calculate the proportion, which adds the base infectious flies to the amount of flies infected by chickens.

Next, we investigated the effect of *base chicken exposure rate* on the KPI *contaminated meat*. The results of the extremes we subjected the model to can be seen in Figure 27. The value used in the baseline is 0.1, and by setting it to 0, we see a decrease in *proportion of contaminated meat* of around 20% in both summer and winter. It nearly reaches a proportion of 0 in winter. When it is set to 0.8, the proportion is, once again, unreal. More than 100% of the meat is contaminated in the summer. This is because there are more *contaminated slaughtered chickens* than *total chickens slaughtered*, which is also something that is impossible in real life. It is caused by the fact that we neglected including a floor function the *CPY-negative chickens* stock. There simply are not enough CPY-negative chickens, and it therefore turns negative. Because of this, a negative amount of chickens are slaughtered with and without cross-contamination, which decreases the *total chickens slaughtered*.

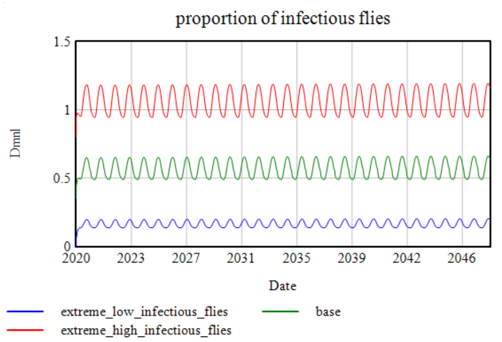

Figure 26: Effect of extreme base infectious flies values on proportion of infected flies

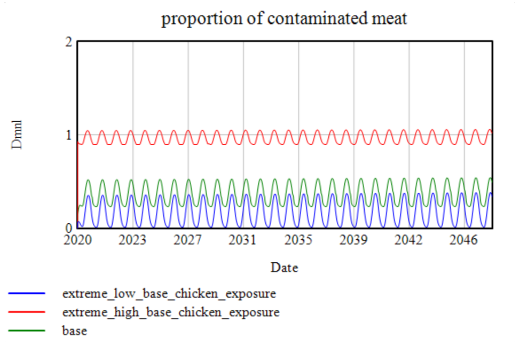

Figure 27: Effect of extreme base chicken exposure rates on proportion of contaminated meat

Finally, we explored the extremes of *CPY reproduction in chickens*. When it is set to the extreme 4, the model reports a proportion of contaminated meat greater than 1, which is an unreasonable proportion. The explanation for this behaviour is similar to the explanation of the previous extreme conditions test: there are more contaminated chickens slaughtered than total chickens slaughtered.This is because the flow *slaughtering without cross-contamination* is always negative, and therefore decreases the *total chickens slaughtered*. The behaviour of this flow is explained by the value of rate of cross contamination, which is around 2.4 in the summer. The reason for this high rate can be directly traced back to CPY reproduction in chickens, which is used as a multiplyer in rate of cross contamination. At the other extreme, we see a decrease in *contaminated meat consumption*, with the most significant difference in summer (a decrease of 40% opposed to 25% in winter). This is simply because there is significant less contaminated meat to consume (about 1 million kg less).

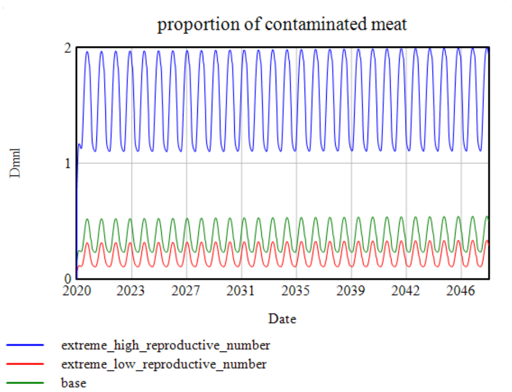

Figure 28: Effect of extreme CPY reproduction on proportion of contaminated meat

B.3 Sensitivity Analyses

To realise the model, we resorted to assumptions, as certain data was unavailable. We were interested in knowing how sensitive the model was to changes in these parameters. We wanted to assess the impact of the parametric changes under all 3 types of scenarios, individually, and combined.

B.3.1 Univariate Sensitivity Analysis

With univariate sensitivity analysis only one parameter was varied at a time, while the other parameters of the system remained constant. We wanted to test all submodels of our system and therefore varied the following parameters: *projected population by 2050*, *temperature increase by 2050*, *temperature switch*, and *rate of symptomatic case modifier*. The first parameter determines population growth, the second parameter determines the maximum temperature of the next 30 years, the third parameter determines how temperature is expected to increase, and the laast parameter how many people will actually show symptoms when infected with *Campylobacter*.

B.3.1.1 Population growth

Based on population projections (NIDI & CBS, 2020) we ran the sensitivity analysis and got the results in figures 29, 30, 31, and 32. Because a population increase also increases demand for chicken, generating a reaction across the model than can be appreciated in the increased contaminated chicken meat stock as well. Because more people get infected in total and present symptoms, the cost of illness also increases.

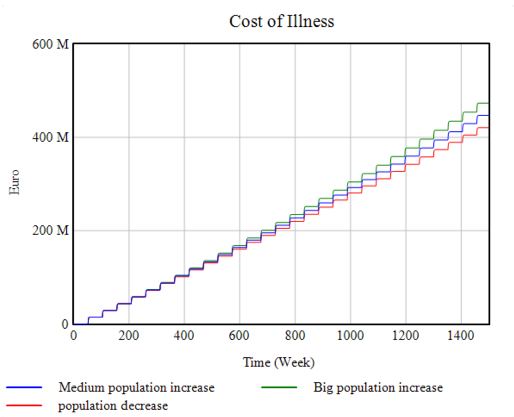

Figure 29: Cost of Illness in the different population scenarios

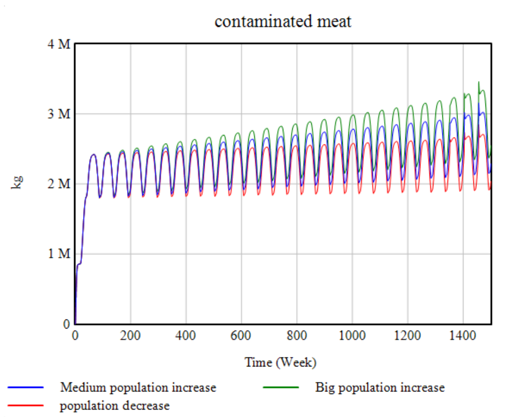

Figure 30: Contaminated chicken meat in the different population scenarios

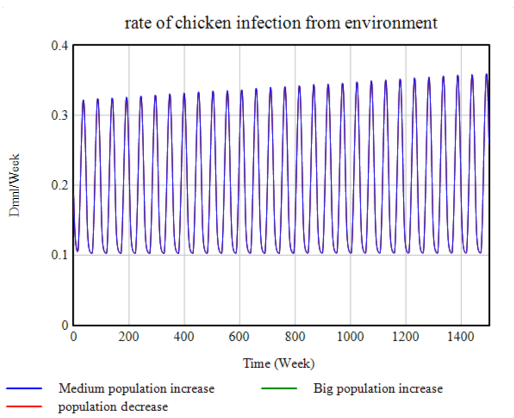

Figure 31: Chicken infections from environment in the different population scenarios

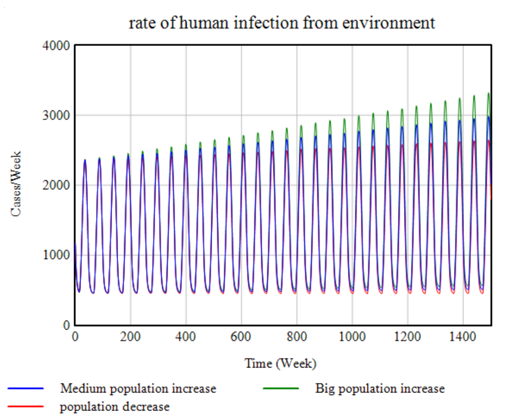

Figure 32: Human infections from environment in the different population scenarios

B.3.1.2 Average temperature increase

Based on climate change projections (KNMI, 2015) we ran the sensitivity analysis and got the results in figures 33, 34, 35, and 36. Temperature increasing aids in the development of disease vectors, which has a direct impact on human infections, besides also affecting indirectly through the food borne route of transmission. This results in increased cost of illness proportional to the increase in temperature over the years.

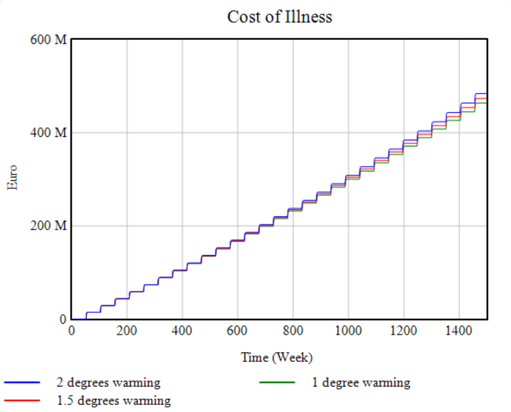

Figure 33: Cost of Illness in the different temperature increase scenarios

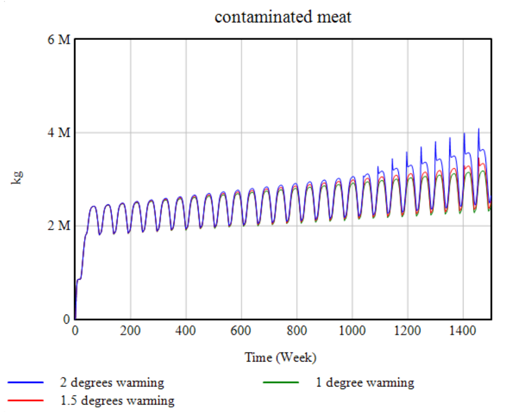

Figure 34: Contaminated chicken meat in the different temperature increase scenarios

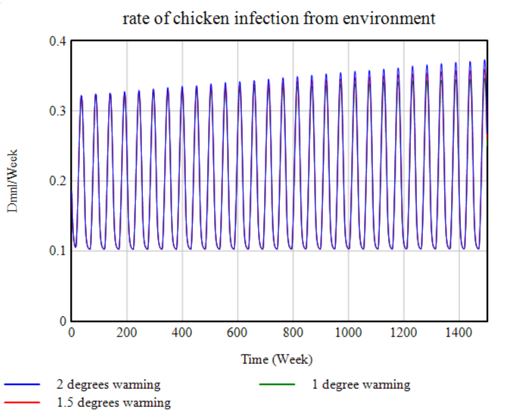

Figure 35: Chicken infections from environment in the different temperature increase scenarios

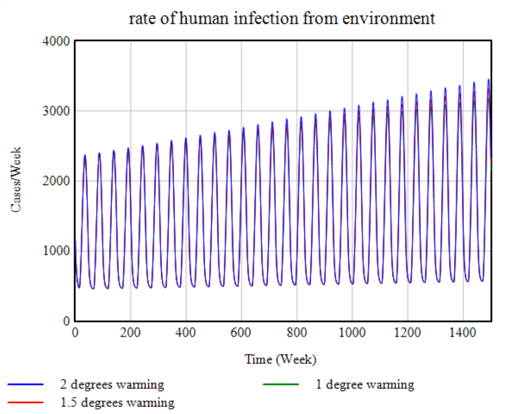

Figure 36: Human infections from environment in the different temperature increase scenarios

B.3.1.3 Seasonal temperature increase

There is uncertainty in how the temperature might increase in the future. It seems that the increase is not uniform throughout the year, but that instead summers might warm up faster than winters. We modelled this uncertainty and compared the scenarios. The seasonal variation in temperature increase leads to longer warmer periods compared to cold periods, which also affects disease vector propagation and has an impact in infections and subsequently in the cost of illness. This can be appreciated in figures. 37, 38, 39, and 40.

B.3.1.4 Rate of symptomatic infections

On figure 41 we can see the result of rate of symptomatic infections changing, which is a behaviour that has been observed recently (Medema et al., 1996). This only bring changes to the cost of illness, as infections remain the same across the model, but the severity of the disease requires more treatment.

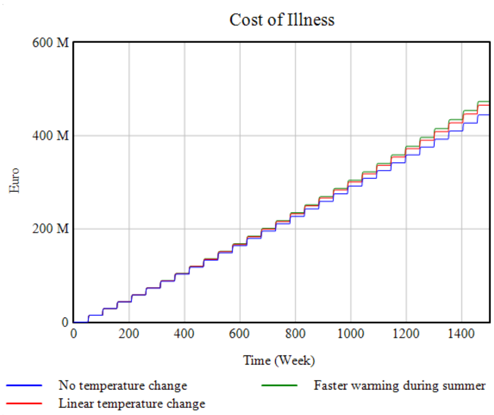

Figure 37: Cost of Illness in the different temperature seasonality scenarios

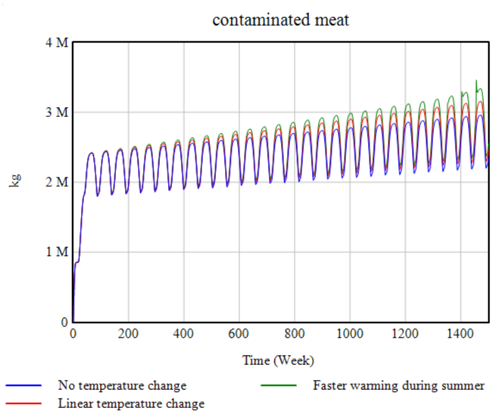

Figure 38: Contaminated chicken meat in the different temperature seasonality scenarios

Figure 39: Chicken infections from environment in the different temperature seasonality scenarios

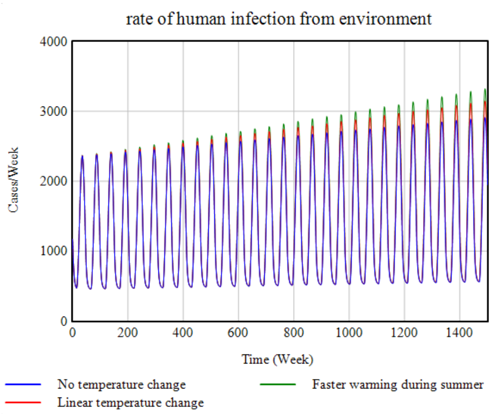

Figure 40: Human infections from environment in the different temperature seasonality scenarios

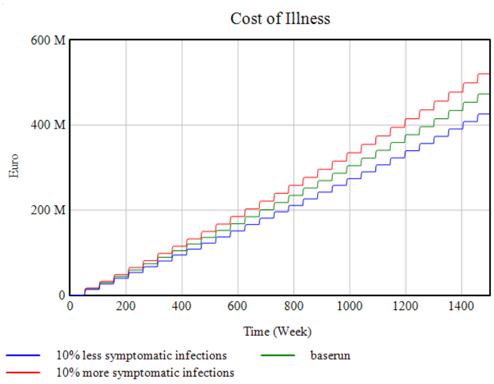

Figure 41: Cost of illness in the different symptomatic infection scenarios

B.3.2 Multivariate Sensitivity Analysis

We ran multivariate analysis to account for the compounded effect of different uncertainties, and the results can be found in Figures 42, 43, 44, and 45. We employed VenSim's built-in Sensitivity feature and let it run 200 simulations. We assigned certain parameters a maximum of 110% of their original value, and a minimum of 90% of their original value. The parameters we subjected to this were: *temperature increase by 2050*, *projected population by 2050*, *temperature switch*, *rate of symptomatic cases modifier*, *COI modifier*. The *COI modifier* was a variable we built in purely for the Multivariate Sensitivity Analysis, as it is uncertain whether the costs for treating the chronic conditions changes overtime. The observed change is mostly regarding numerical sensitivity, but we can see that the contaminated chicken meat can overshoot at times, which is the result of people refusing to eat meat as a result of increased infections, but the chicken were already in the production cycle so there was excess production.

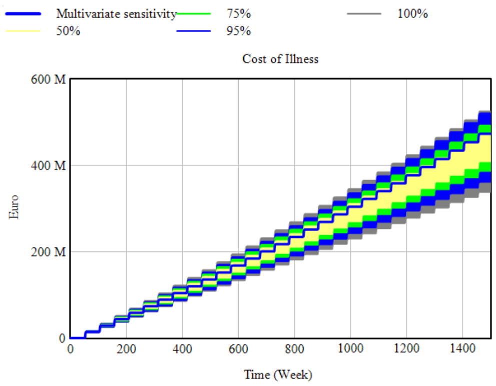

Figure 42: Cost of Illness in the multivariate analysis

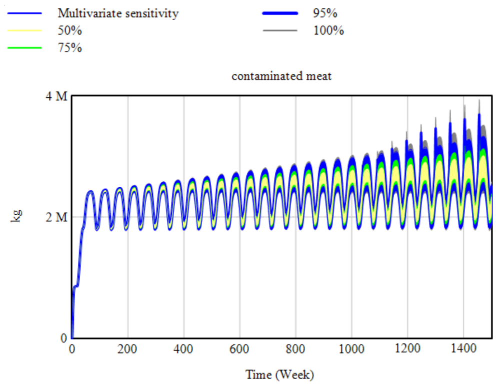

Figure 43: Contaminated chicken meat in the multivariate analysis

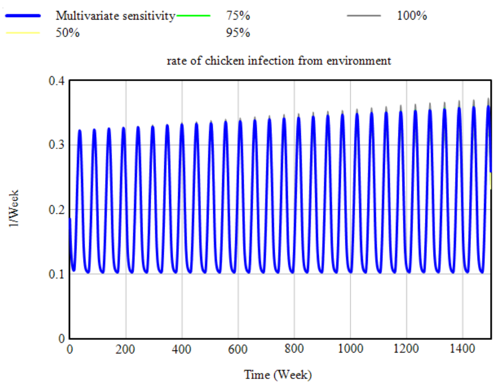

Figure 44: Chicken infections from environment in the multivariate analysis

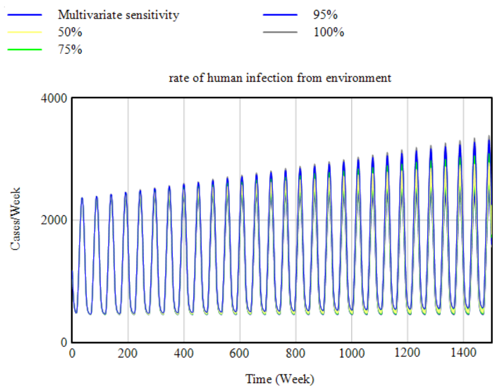

Figure 45: Human infections from environment in the multivariate analysis

B.4 Comparison to real world data

Vlaanderen et al. (2019) estimated there were around 71.000 cases of Campylobacteriosis in the Netherlands in 2018, 67.000 in 2017 and 79.000 in 2016. We plotted the amount of cases produced by our model against the average of these three values. The results can be seen in Figure 46. We can see the stock in our model is a good reflection of the real world.

NEPLUVI (2019) monstered broiler chickens weekly in 2018, and found 41, 9-58.1% of broiler chickens were tested positive for *Campylobacter*. This concerns chickens from slaughterhouses. As can be seen in Figure 47, our base model has similar values for each year.

In the Netherlands the (unsanitary) preparation and/or consumption of chicken were attributed to 20-30% of infections in 2018. However, around 50-80% of cases can be attributed to *Campylobacter* strains associated with poultry (Cuperus et al., 2020; NEPLUVI, 2019). Therefore, it is safe to assume that there are multiple transmission routes. We assume the biggest transmission routes can be found in the environment. In the base model, around 5.77% of the infections stem from the preparation and/or consumption of chicken. This can be seen in Figure 48. It may be the case that the environment plays a bigger role than we previously assumed, after all, it is easier to trace back the cause to undercooked meat than to a wild bird.

Numbers on the average amount of chicken meat consumption per Dutch person differ, but they are between 0.22 and 0.47 kg of chicken meat per week (Schotman, 2018; Waveningen University & Research, 2020). In our model this fluctuates between 0.153 and 0.203 so there is a slight discrepancy.

We also validated our DALYs and Cost of Illness against the data points from (Mangen et al., 2007). Note that these values are from 2007. As can be seen in Figure 49 our model determines higher DALYs than given in the literature. This may indicate that there are more chronic diseases that can be traced back to *Campylobacter* than is currently happening in the real world. Perhaps the specialists are overlooking the bacterium as a cause, or they are simply unable to pinpoint the cause.

In Figure 50 it can be seen that the Cost of Illness calculated by the model is lower than Mangen et al.'s values. This is probably due to the fact that we only look at 3 chronic conditions and the acute conditions.

It is estimated there are around 17 million species of *Diptera* per person (Gorman, 2017). We are only interested in *Musca domestica*. It is unknown what their numbers are in the Netherlands, and we are unable to estimate. However, it has been guessed that the population of Houseflies will increase by 244% by 2080 (McAlister, 2017). In The amount of flies in our model after 1 year is 20.000 of which 7.700 are infectious (TIME STEP = 0.0625). This is probably not a proper reflection of the real world, but one can assume that it is only 7.700 flies that have directly caused a disease in humans and/or chickens.

The model also includes an Infection risk from birds (2.5e-05). There are about 1.3 million birds in the Netherlands ("Miljoenen vogels boven Nederland", 2019). There was no literature on the risk from birds, so we assumed a somewhat safe value. We doubt *Campylobacter* will ever be exterminated due to the presence of these environmental factors, even if we are somehow able to keep our farms, slaughterhouses and stores free from *Campylobacter*.

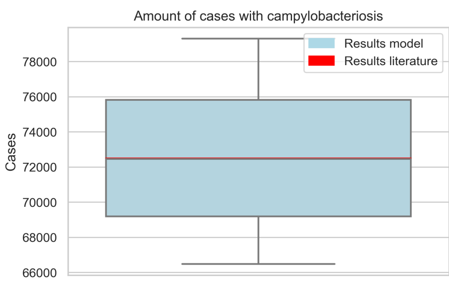

Figure 46: Validation of human cases

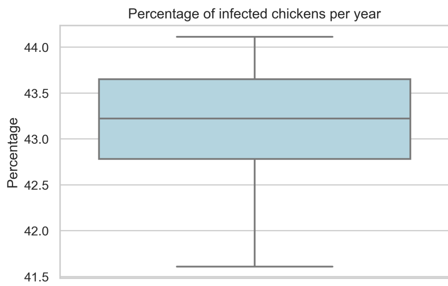

Figure 47: Validation of proportion infected chickens

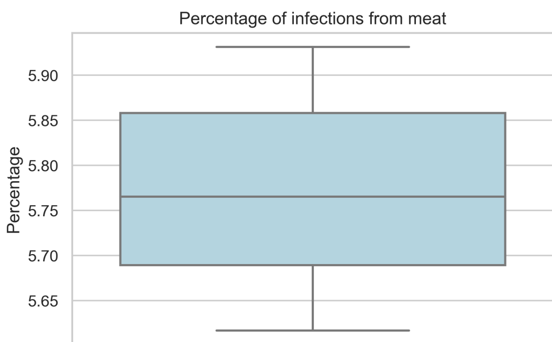

Figure 48: Validation of sources of Campylobacteriosis

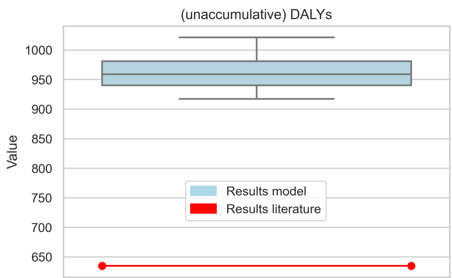

Figure 49: Validation of DALYs

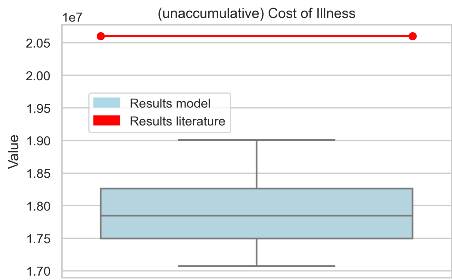

Figure 50: Validation of Cost of Illness

C Details on policies and experiments

To answer our research question, experiments were set up around the three components in the research question: climate, population and public health.

The structural and parametric uncertainties resulted in five policies that will be tested. These policies were designed based on reality and are capable of providing a view of the policies' cost effectiveness and robustness. These policies will be discussed in Subsection C.1 to C.2.

We elaborate on the scenarios used to test these policies in Subsection C.3.

C.1 Environmental factors and policies to control disease vectors

Two policies were implemented with regards to environmental factors and the biological disease vectors. Both are triggered by temperature, as this is the main driver of the population growth of flies, as explained in Section 3.

C.1.1 Exposure control policy

This policy decreases human exposure to infected flies: on the season when the disease vector is more prevalent, public campaigns will urge the population to keep organic waste properly closed and use fly nets (Hald et al., 2007). Similar measures are used to prevent the spread of disease carrying mosquitoes in tropical countries (Govella & Ferguson, 2012).

The closed-loop policy is triggered by the temperature. If the temperature is above 20°c, the policy goes in effect. This temperature is based on the findings by Schou et al., 2013. It assumes an immediate reduce of 20% on the rate of human exposure to infectious flies. It was also assumed there would be an information delay of 2 weeks from the onset of the policy to full implementation.

C.1.2 Fly population control policy

When a certain threshold of fly population is reached, the government can initiate extermination campaigns to limit the spread of diseases. This can be generalised, or localised only around farms.

Likewise to the Exposure control policy, this policy is activated by temperature. Once the temperature gets above 20°c, the policy goes into effect. This immediately reduces the fly population to 80%. We assume the effect is immediate, as this policy is not dependent on people's behaviour: the government can instantiate these immediately.

C.2 Food safety behaviours and policies

With regards to food safety behaviours and policies, we looked at two insertion points in the chicken production cycle: the hygiene of the slaughtering process and the way food is handled from the slaughterhouse to the consumer. Lastly, we also looked at the effectiveness of a policy that addresses consumer behaviour by discouraging meat consumption.

C.2.1 Safe slaughtering Policy

This policy would try to address and improve the level of hygiene of slaughterhouse process and equipment, which has been identified to be a major transmission. Specifically this policy would for instance require slaughterhouse equipment to be cleaned using water that is frequently changed to prevent cross-contamination. This can also be enhanced by the use of UV radiation to aid in the decontamination process without altering the sensory quality of the meat (Isohanni & Lyhs, 2009).

In the model this was implemented by adding a switch variable that turned on if the COI of the the previous year exceed a certain amount, in this case set to €15 million, to reduce the *rate of cross-contamination cross-contamination* by 20%. It is of note that the switch activates the modifier immediately upon reaching the threshold, thus operating under the assumption that there is no delay in policy trigger and its implementation. In reality it will take time to adopt the policy, but effects are negligible at the 30-year time scale.

C.2.2 Food safety and handling policy

This policy deals with the way chicken products are handled by both consumers and actors in the production cycle of chicken meat. If the quality of the routines in the preparation, transport and storage of chicken products is increased, there will be a reduction in foodborne illnesses such as campylobacteriosis (Shane, 2000).

When the Cost of Illness of past year has exceeded the threshold value of €15 million, this policy is triggered. So, effectively, there is a delay of 1 year. There is 20% less chance to get infected by the consumption of meat once this policy is in effect.

C.2.3 Consumption behaviour policy

With this policy, instead of attempting to disrupt *Campylobacter* transmission routes among chickens and other animals, it circumvents the central issue and addresses meat consumption. This would include any measure that would dissuade or restrict the consumption of chicken meat throughout the population, e.g. campaigns, meat tax, etc.

The policy also operates with a threshold-activated switch. The threshold was set higher to €22 million compared to the safe slaughtering policy, as it is seen as "last resort", because it seems unlikely that meat bans would be complied to, nor be implemented in the first place, as meat consumption in the Netherlands is still on the rise.

C.3 Details on experiments

The policies employed in the model were tested against twelve scenarios, as detailed in Table 6. Scenarios 0, 1, 5 and 9 have the same values and are all baselines. The baseline simply contains a population increase that is also the medium increase, a temperature increase of 1.5 °c, a linear temperature change, and no rate of symptomatic cases modifier.

Table 6: Scenarios under which the policies were tested for robustness

Test		Variable to change				
		Scenario number	Population increase by 2050	Temperature increase by 2050	Temperature switch	Rate of symptomatic cases modifier
	Baseline	0	1,94E+07	1.5	1	1
Population	Medium increase	1	1.94E+07	1.5	1	1
	Large increase	2	2.16E+07	1.5	1	1
	Decrease	3	1.71E+07	1.5	1	1
Temperature Change	1 degree	4	1.94E+07	1	1	1
	1.5 degree	5	19.4E+06	1.5	1	1
	2 degree	6	19.4E+06	2	1	1
Seasonality	No temp change	7	19.4E+06	1.5	0	1
	Fast temp change	8	19.4E+06	1.5	2	1
	Linear temp change	9	19.4E+06	1.5	1	1
Public Health	10% fewer symptoms	10	19.4E+06	1.5	1	0.9
	10% more symptoms	11	19.4E+06	1.5	1	1.1
	Worst case	12	2.16E+07	2	2	1.1

D Report log

The working hours of each member of this group were logged, and they are shown in their respective subsections.

D.1 Elias Bach

Elias was a member of this group and his contributions are shown in Table 7.

Table 7: Elias' report log

Date	Hours	Task
09-02	1.5	Meeting with group, create bull's-eye diagram, wrote notes on scope
10-02	1	Meeting with group
11-02	1.5	Reviewed Q4 of assignment 1, made an SSD diagram draft
12-02	1	Meeting with team and divided tasks for Sunday
12-02	0.5	Figured out how to work with submodels and views in Vensim
12-02	2	Recreated submodels 1 and 3 in Vensim
18-02	1	Introduction for assignment 2
19-02	1	Meeting to discuss assignment 2
19-02	2	Introduction for assignment 2
20-02	2	Introduction for assignment 2
21-02	1	Introduction for assignment 2
24-02	1	Introduction/methods for assignment 2
25-02	1.5	Group meeting
25-02	1	Methods for assignment 2
26-02	0.5	Team meeting and final edit for A2
27-02	0.5	Peer review
28-02	1	Peer review
29-03	0.5	Peer review
04-03	1	Group meeting
07-03	2	Worked on environmental submodel
09-03	1	Worked on environmental submodel
10-03	2	Worked on environmental submodel with Lisette
11-03	5.5	Group meeting for modelling
18-03	6.5	Group meeting for modelling
20-03	1	Group meeting with Emily & Lisette about structural uncertainty
21-03	1.5	Group meeting with Emily & Lisette about structural uncertainty
22-03	1	report writing
24-03	1	model verification and reporting
25-03	1	policy brainstorming and minor report adjustments
26-03	6	Improved model with group, experimented with policies with Lisette, and worked on validation
29-03	1	group meeting for peer review and dividing tasks
30-03	0.5	peer review
04-04	1	Experimentation
05-04	1	Reporting w/ Menghua
06-04	2	group meeting and running experiments

07-04	6	Campus meeting
08-04	3	writing report
09-04	1	finalising report

D.2 David Matheus

David's contributions are shown in Table 8.

Table 8: David's report log

Date	Hours	Task
09-02	1.5	Team meeting, drafted model purpose.
10-02	1	Team meeting, reviewed work.
11-02	0.5	Drafted conceptual model about fly infection loop.
12-02	1	Team meeting, divided tasks for Sunday.
16-02	0.75	Team meeting, reviewed assignment 1 and divided tasks.
18-02	1	Team meeting, reevaluation of model aggregation.
18-02	2.5	Meeting with Menghua, stocks and flows model.
18-02	0.5	Work on stocks and flows model.
19-02	1	Team meeting, discussed changes to conceptualisation and stocks and flows.
19-02	0.75	Work on stocks and flows model.
19-02	1	Meeting with Menghua, stocks and flows model.
23-02	1	Meeting with group, divided tasks for the week.
24-02	0.5	Work on chicken infection sub-model.
25-02	1.5	Group meeting, discussed models and sub-models, assigned tasks.
25-02	1.5	Work on chicken infection sub-model and report writing.
26-02	0.5	Group meeting, review for submission.
27-02	0.5	Peer review group 9b's work.
28-02	0.5	Peer review.
04-03	1	Meeting with group.
08-03	0.25	Updated Lisette on project.
09-03	1.5	Worked on conceptualisation for chicken contamination part of general model.
11-03	4.5	Worked on general model with the group in Wijnhaven.
12-03	1	Worked on conceptualisation for general model.
18-03	6.5	Worked on model with the group at Wijnhaven.
24-03	2.5	Brief team meetings, worked on model and report writing.
25-03	1.5	Meeting, experimental design, remade chicken CLD and wrote report.
26-03	6	Meeting with the group at Wijnhaven, experiment setup, sensitivity analysis.
29-03	0.5	Group meeting.
31-03	1	Group meeting, divided tasks and prepared presentation.
01-04	1	Presentation and group meeting.
02-04	1	Reran sensitivity analysis, prepared consumption behaviour experiment.
04-04	2.5	Corrected errors, reconceptualised behaviour experiment, reran experiment.
05-04	2.5	Detailed revision of model and documentation.
06-04	3	Group meeting, more revision, data export.
07-04	6	Meeting at Wijnhaven, results discussion, extreme conditions, report writing.
08-04	3.5	Brief group meeting, report writing and reviewing.

09-04	1	Meeting with group, last details.

D.3 Menghua Prisse

Menghua was a member of this group and her contributions are shown in Table 9.

Table 9: Menghua's report log

Date	Hours	Task
09-02	1.5	Meeting with group, drafted dynamic hypothesis and synthesised with Lisette's solution
10-02	1	Meeting with group
11-02	1.5	Reviewed and worked on Question 2 of Assignment 1
14-02	1	Reviewed adjustments to Assignment 1 & started for Assignment 2
16-02	0.75	Meeting with group
17-02	0.25	Presentation prep
18-02	3.5	Meeting with group and working on the Stock Flow diagram with David
19-02	2	Meeting with group and working on the Stock Flow diagram with David
21-02	1	Go over what has been written already to become familiar with it
24-02	1	Read up on sewage systems
25-02	1.5	Read over text
26-02	1.5	Meeting with group and going over Introduction and peer review of group 9b
01-03	1	Peer review of group 9b
04-03	1	Meeting with group
07-03	1	Read into new sources and worked on conceptualisation for the general model
10-03	1	Continued work on conceptualisation and discussed COI with Emily
11-03	4.5	Worked on the model with the group
18-03	6.5	Worked on the model with the group
13-03	1	Studied changes to model
24-03	2	Discussed how to continue with the report (morning) and worked on model verification (afternoon)
25-03	4	Worked on model verification, adjusted dynamic hypothesis and helped Lisette (not all hours were productive)
26-03	6	Adjustments to model and worked on the report
30-03	0.5	Going over peer review
31-03	1	Split tasks and made presentation
01-04	1.5	Presentation and group meeting and planned own tasks
03-04	1	Went over variable spreadsheet
05-04	3	Met with Elias, did tasks: adjusted model, added food safety policy and worked on spreadsheet
06-04	5	Met with Emily to restructure report (morning) and meeting with group, tried to run experiments, analysed results in the evening (not all hours productive)
07-04	6	Met with group to finalise report
08-04	4	Met with Irene and worked on finalising report
09-04	2	Final report review

D.4 Emily Ryan

Emily was a member of this group and her contributions are shown in Table 10.

Table 10: Emily's report log

Date	Hours	Task
09-02	1.5	Meeting with group and draft subsystem diagram
10-02	1	Meeting with group
12-02	1.5	Meeting with group and draft KPIs/dynamic hypothesis
14-02	2.5	Final editing and write-up for Assignment 1
16-02	1	Meeting with group and planning work
17-02	0.5	Presentation slides for first review
18-02	2	Team meeting, presentation and report writing
19-02	2	Team meeting and report writing
21-02	2	Report writing
23-02	3	Team meeting and conceptualising COI sub-model
25-02	3	Report writing and Team meeting
26-02	1.5	Finalise COI text, update dynamic hypothesis and team meeting
04-03	4	Team meeting and identifying values for COI submodel
05-03	1	Research and further conceptualisation COI and disease burden submodels
09-03	2	Research and valuation for COI submodel and update Lisette
10-03	1.5	Reconceptualise COI and disease burden model for model-building
11-03	4.5	Working on model with the group
15-03	1.5	Report writing
18-03	6.5	Working on model with the group
20-03	1	Worked on the model with Elias and Lisette and discussed structural uncertainty
21-03	1	Group meeting with Lisette and Elias
23-03	2	Report writing
24-03	1	Meeting with group and report writing
25-03	2	Meeting with group and report writing
26-03	7	Meeting with group - report writing and modelling
29-03	1	Meeting with group and group 9b review
30-03	1	Review group 9b and prepare task list
31-03	0.5	Finalise final task list for group
01-04	1.5	Presentation review and meeting with group
02-04	2	Generating model runs and scenario plan and pest control scenario
05-04	2	Write up preliminary policy interpretation, update methods section
06-04	4	Meetings to review results and re-running scenarios
07-04	6	Meeting/working session with team to finalise results
08-04	7	Meeting with team, writing up final sections
09-04	2.5	Final report review and submission

D.5 Lisette de Schipper

Lisette was a member of this group and her contributions are shown in Table 11.

Table 11: Lisette's report log

Date	Hours	Task
08-02	1	Set up Zotero, Github and Overleaf
09-02	1.5	Meeting with group, created dynamic hypothesis and sketched expected behaviour of KPIs
10-02	1	Meeting with group
11-02	1	Reviewed and improved the answer to question 1 of assignment 1
12-02	1.5	Meeting with team and divided tasks for Sunday, figured out how to work with submodels and views in Vensim
13-02	0.5	Recreated submodels 2 and 4 in Vensim
16-02	0.75	Meeting with group, collectively reviewed assignment 1, and divided tasks
18-02	2.5	Meeting with group, attended presentation for Jill and Irene, reflected with group on feedback, gave tutorials on Zotero, and started working on introduction, improved dynamic hypothesis
19-02	1.5	Meeting with group, discussed dynamic hypothesis & conceptualisation, worked on introduction, included glossary
20-02	0.75	Continued working on introduction
23-02	1.5	Continued working on introduction and meeting with group
24-02	2	Started construction + research of the environmental submodel
25-02	3	Meeting with group and continued working on environmental submodel
26-02	1.5	Continued working on environmental model and meeting with group
27-02	1	Worked on peer review of group 9b
28-02	1.5	Worked on peer review of group 9b
08-03	0.25	Got updates on project from David
09-03	0.5	Got updates on project from Emily
10-03	2	Worked on environmental submodel with Elias
11-03	4	Worked on the model with the group
18-03	4	Worked on the model with the group
20-03	1	Worked on the model with Elias and Emily and discussed structural uncertainty
23-03	0.5	Worked on model and on report
24-03	1.5	Met with group and worked on validation
25-03	5	Worked on validation, redesigned the diagram of the environmental submodel, wrote in report, made additions to model, met with group
26-03	6	Improved model with group, experimented with policies with Elias, and worked on validation
27-03	1	Improved some plots
28-03	2	Worked on validation
29-03	1	Met with group and worked on validation
30-03	1.25	Reviewed Group 9b
31-03	1	Prepared presentation & divided remaining work
01-04	1.5	Polished presentation, dealt with errors in report & presented with group and discussed new insights
02-04	1	Incorporated the scenario switch + slider, ran policy experiments, and wrote about the fly exposure policy in the report
03-04	3	Video meeting with Emily to talk about report, a worst-case scenario, and additional delays in implementations of policies, implemented delay in implementation and reran experiments & worked on visualisations

04-04	1.5	Worked on automation of visualisations, met with David to talk about the consumption policy, & met with Elias to explain the views and sliders
05-04	1.5	Reran fly exposure policy and base model w/o policies, included baserun and DALYs in the visualisation notebook, included visual feedback in the simulation view & discussed structure of model with Elias
06-04	5	Met with group, automated getting the visualisations, met with Elias, met with Emily, helped with gathering data from Vensim, moved a large portion of validation to appendix, & included the current model documentation in report
07-04	7	Worked with the team on Wijnhaven, and made some additional visualisations at home
08-04	6	Met with team & Irene, worked on report and visualisations.
09-04	2	Polishing the report