











Exploitation of challenge testing in exposure assessment of foodborne pathogens

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Objectives

You will learn:

- The types of microbial exposure assessment and the requirements to conduct one
- The key aspects for consideration when building an exposure assessment model
- How to exploit challenge test data when building an exposure assessment model
- How to make use of predictive microbiology models or kinetic parameters when building an exposure assessment model
- How to conduct a step-by-step analysis to incorporate growth and inactivation models in an exposure assessment model programmed in R

Materials needed:

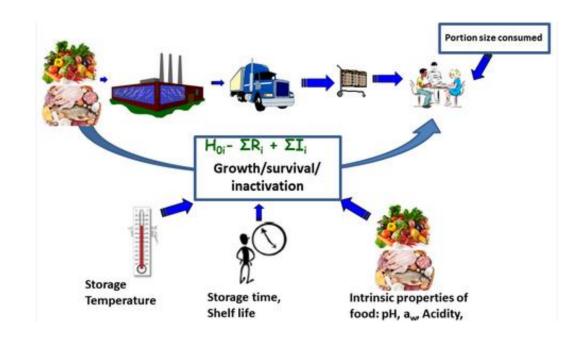
- This presentation
- Three R scripts: StirFry_MildHeat.R, StirFry_Storage.R, StirFry_Baseline.R
- The accompanying video

Content

- Microbial exposure assessment
 - Definition, requirements, types
- Model development
 - Key aspects, conceptual model
- Growth and inactivation models in exposure assessment
 - Critical features, use of challenge test data, use of kinetic models/parameters
- An example of use of growth/inactivation models in exposure assessment
 - Conceptual model
 - Baseline scenario in R

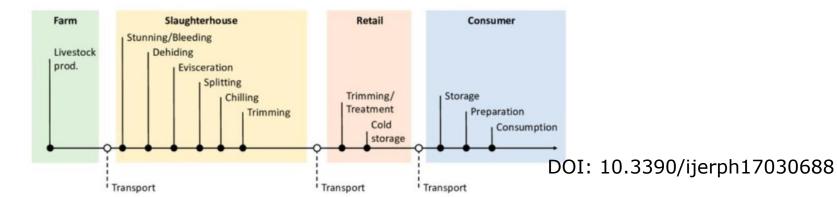
Microbial exposure assessment

- Definition
- Requirements
 - Types



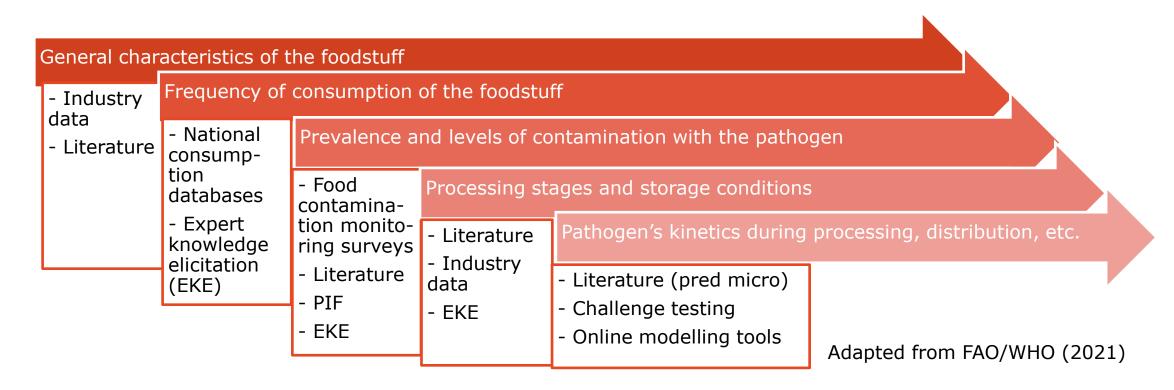
Microbial exposure assessment

- Microbial exposure assessment is the **qualitative** and/or **quantitative** evaluation of the likely intake of a microbial hazard via specific foods
- The exposure assessment should describe the pathways of exposure that are relevant to the risk assessment:
 - If the purpose was to compare strategies from production to consumption, then the various stages from **farm to fork** should be assessed
 - If the purpose was to assess the effects of consumer handling, then only the pathway from **retail to consumption** may be relevant

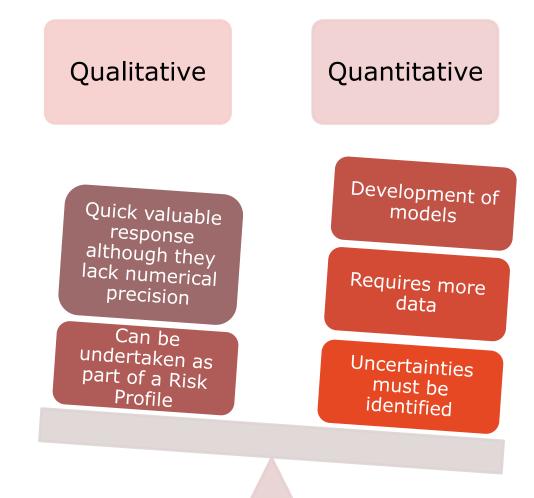


Requirements for microbial exposure assessment

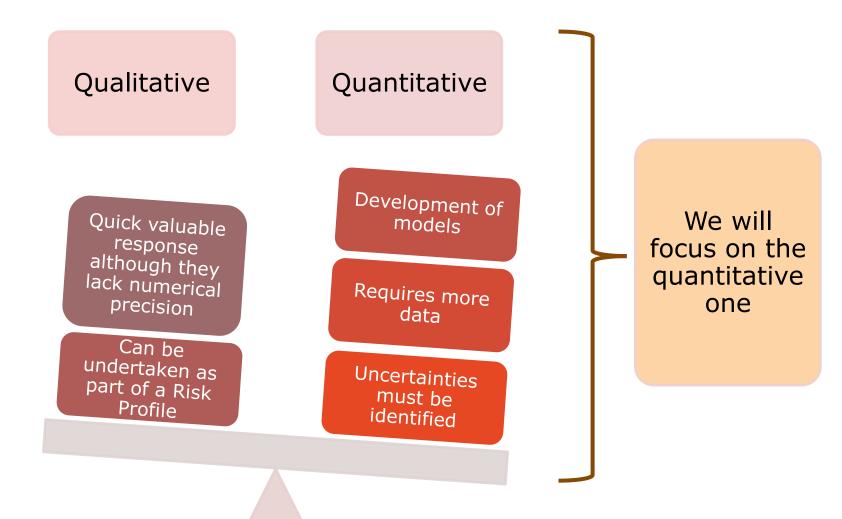
 One must consider the factors that have a direct effect on the consumer's exposure to the hazard



Types of microbial exposure assessment

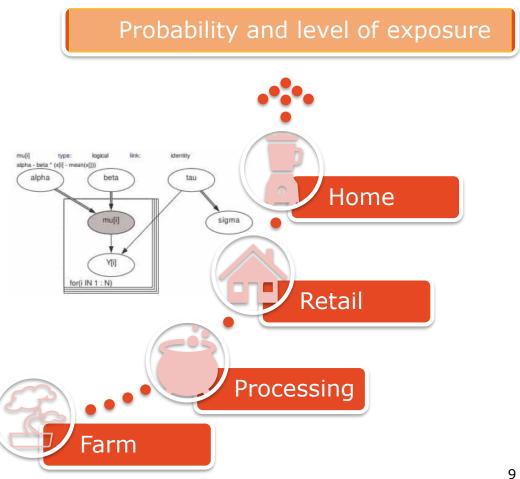


Types of microbial exposure assessment



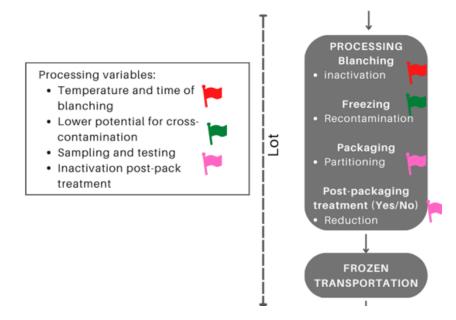
Quantitative microbial exposure assessment

- The goal from the quantitative exposure assessment is to deduce, from the available information, the probability and magnitude of the exposure to the hazard
- Exposure data characterising the occurrence of the microbial hazard in food at the point of consumption is usually not available.
- Thus, an exposure assessment model will estimate prevalence and concentration in a food serving

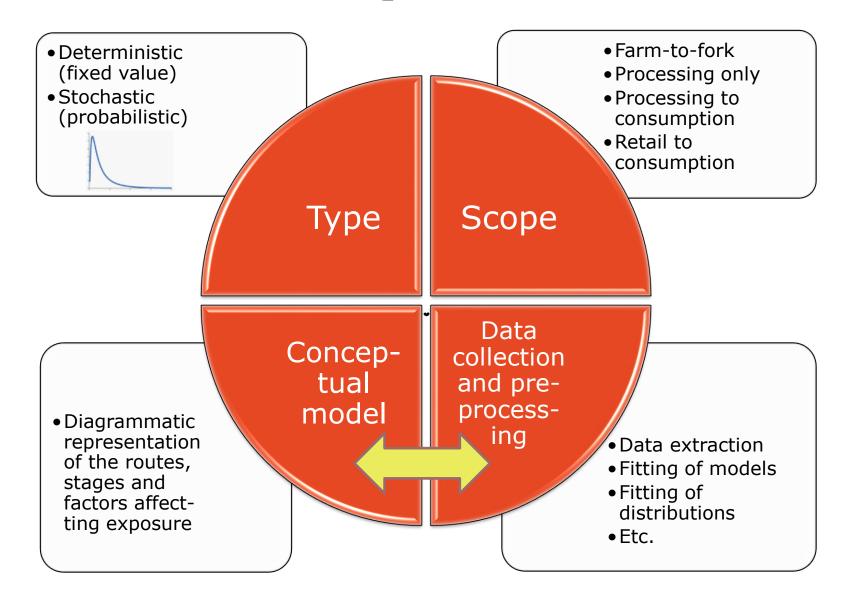


Model development

Key aspectsThe conceptual model

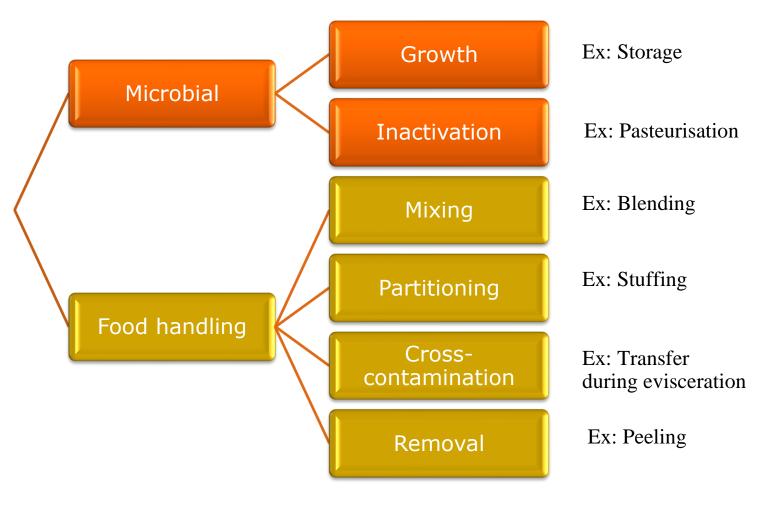


Key aspects of model development



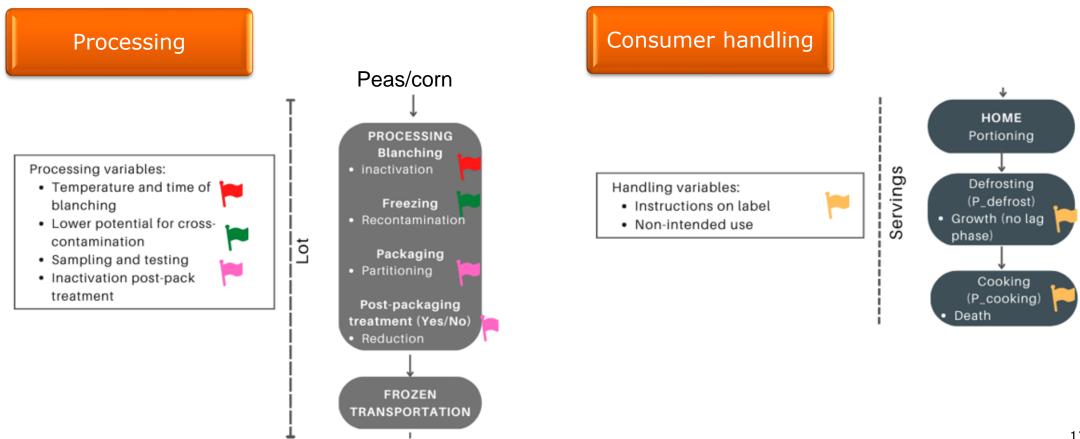
Conceptual model

- Often based on the Modular Process Risk Model (MPRM, Nauta et al., 2002)
 - There are two types of processes: microbial processes and food handling processes
 - At least one of them should be assigned to the modelled stages



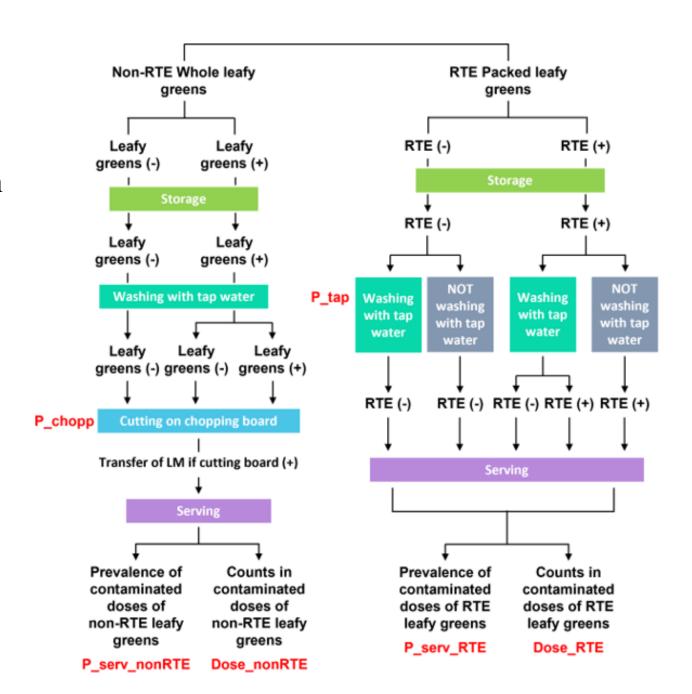
Conceptual model

An example of MPRM sketch for frozen corn/peas to be modelled from processing to consumption



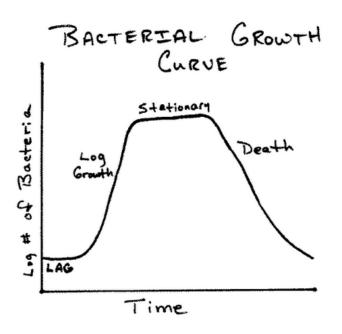
Conceptual model

- An example of home preparation module non-RTE and RTE leafy greens
 - Event tree sketch



Microbial growth/inactivation models in exposure assessment

- Critical features
- Use of challenge testing data
- Use of kinetic models/parameters



Application of kinetic models/parameters in exposure assessment

Some features are critical to the utility of predictive microbiology models

Range of independent variables to which the model applies
(Avoid extrapolation, for example, by trimming extreme temperatures)

Sources of variability and uncertainty
(Identify the microbial parameters subject to variation, and which variation)

Effect of spoilage microbiota on shelf life of the product
(Contaminated foods that become spoiled will not be consumed)

Validated sources!



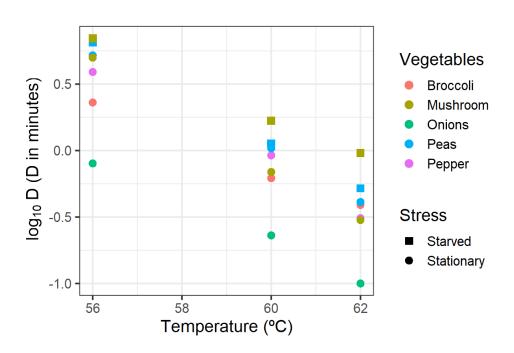
• Suppose that we need information on the inactivation of *L. monocytogenes* in raw vegetables, and we found the following "readily extractable" data from the literature

TABLE 1. Heat resistance of L. monocytogenes in different vegetables

| Vegetable | | D-value (min) at temperature of: | | | _ |
|-----------|------------------|----------------------------------|-----------------|-----------------|--------------|
| | Condition | 56°C/133°F | 60°C/140°F | 62°C/144°F | |
| Onions | Stationary phase | 0.8 ± 0.07 | 0.23 ± 0.09 | 0.10 ± 0.03 | |
| Broccoli | Stationary phase | 2.3 ± 0.21 | 0.62 ± 0.03 | 0.39 ± 0.05 | |
| Peppers | Stationary phase | 3.9 ± 0.35 | 0.92 ± 0.08 | 0.31 ± 0.01 | |
| Mushroom | Stationary phase | 5.0 ± 0.43 | 0.69 ± 0.06 | 0.30 ± 0.03 | |
| Mushroom | Starved | 7.0 ± 0.35 | 1.68 ± 0.11 | 0.96 ± 0.13 | |
| Peas | Stationary phase | 5.2 ± 0.28 | 1.04 ± 0.14 | 0.41 ± 0.08 | |
| Peas | Starved | 6.5 ± 0.21 | 1.13 ± 0.10 | 0.52 ± 0.06 | (Mazzotta, 2 |

• How can we use these data to model inactivation parameters for exposure assessment?

- Decisions to make:
- 1) Confidence about the data
- 2) The model



The Bigelow model can be used

$$\log_{10} D = \log_{10} D_{ref} - \frac{(Temp - T_{ref})}{z_T}$$
 $T_{ref} = 70$

```
41
     bigelow_vegetables<-function(Temp,Tref,log10Tref,zT)</pre>
43 - {log10DT<-log10Tref-((Temp-Tref)/zT)
44 return(log10DT)
45 - }
   ## 2.1 Simple nls fit
   fitmodel1<- nls(log10D~bigelow_vegetables(Temperature,Tref=70,log10DTref,zT),
                   start = list(log10DTref=-1.5,zT=10),
52
53
                   upper=c(4,10),
54
                   lower=c(-3,0.01),
55
                   data = data
56
                   algorithm="port",
57
                   trace=TRUE)
58 summary(fitmodel1)
                                                                        TΩ
```

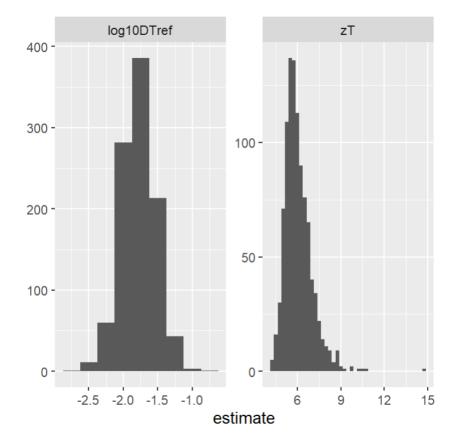
3) Sources of variability:

- Heat resistance parameters:
 - **Between-strain variability?** mixed effects
 - **Between-vegetable variability?** mixed
 - **Uncertainty?** fixed effects
- This decision depends on the amount of data available and the complexity to add to the model
- We will opt for modelling only the uncertainty about the estimate(s)

3) Sources of variability:

```
71 ## 2.3 Bootstrap using broom package
72 - fit_nls_on_bootstrap <- function(split) {
      nls(log10D~bigelow_vegetables(Temperature,Tref=70,log10DTref,zT),
          analysis(split), start = list(log10DTref=-1.5,zT=6))
74
75 ^ }
76
   boot_models <- boots %>%
      mutate(model = map(splits, fit_nls_on_bootstrap),
79
             coef_info = map(model, tidy))
80
    boot_coefs <- boot_models %>%
      unnest(coef_info)
82
83
    alpha <- .05
    boot_coefs %>%
86
      group_by(term) %>%
87
      summarize(low = quantile(estimate, alpha / 2),
                high = quantile(estimate, 1 - alpha / 2))
88
89
    boot_coefs %>%
91
      group_by(term) %>%
92
      summarize(mean_log10 = mean(estimate),
93
                sd_log10 = sd(estimate))
94
    ggplot(boot_coefs, aes(estimate)) +
      geom_histogram(binwidth = 0.25) +
      facet_wrap(~ term, scales = "free")
```

 Bootstrapping techniques allow building an uncertainty distribution about the fitted parameter



• Two options are possible:

-2.5 -2.0 -1.5 -1.0

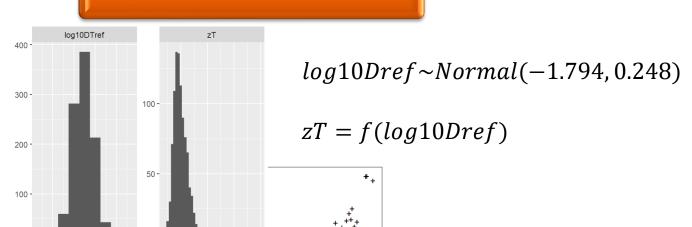
9

2

Complex: 2 uncertainties

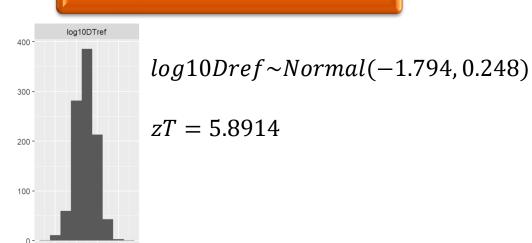
-2.0

-1.5



These parameters are correlated!

Simple: 1 uncertainty



-2.5 -2.0 -1.5 -1.0

4) The stochastic function of mild heat treatment MildHeat() for exposure assessment

Initial concentration

$$C_0 \sim xxx$$
 log CFU/g

Heat treatment conditions

$$Time \sim Pert(1, 3, 7) min$$



Hyperparameters and inactivation model

$$log10Dref \sim Normal(-1.794, 0.248)$$

$$\log_{10} D = \log_{10} D_{ref} - \frac{(Temp - 70)}{5.8914}$$

Output

$$C_f = C_0 - \frac{Time}{D}$$

5) Testing the function

Initial concentration (contaminated fraction)

$$C_0 \sim Normal(0.8, 0.3) \log CFU/g$$



Heat treatment conditions

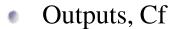
$$Time = 1.5 min Temp = 68 °C$$

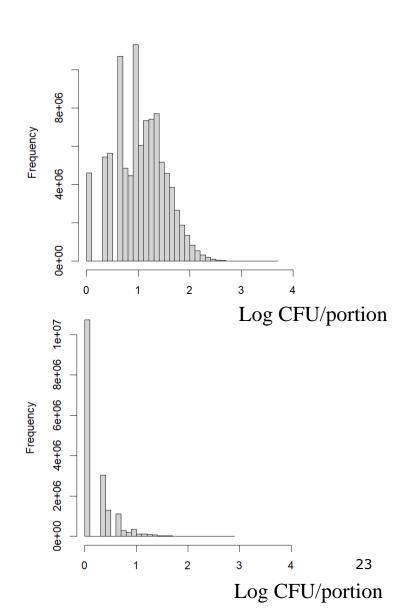
Initial concentration (contaminated fraction)

$$C_0 \sim Normal(0.8, 0.3) \log CFU/g$$

Heat treatment conditions

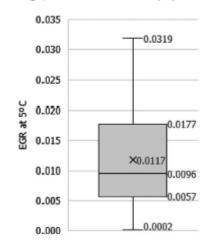
$$Time = 3 \min$$
 $Temp = 68 \, {}^{\circ}C$

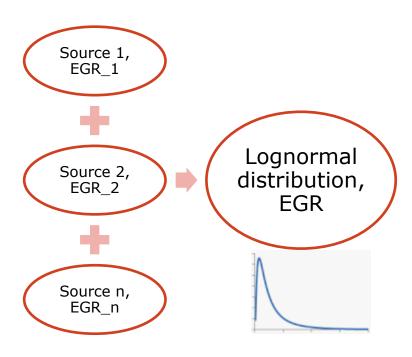




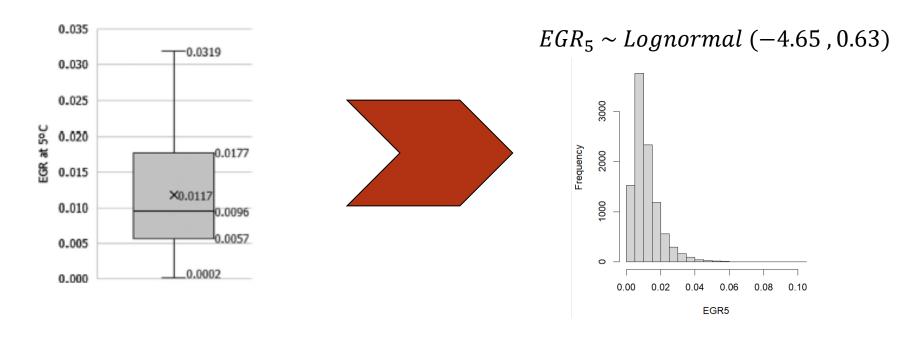
• Suppose that we need information on the growth of *L. monocytogenes* in heat-treated vegetables, and we found a synthesis of data collected from the literature. How can we use this information?

Figure 5 shows the distribution of the **exponential growth rate** at 5° C (EGR_{5°C}, \log_{10}/h) using data collected from scientific literature and Combase records reporting *L. monocytogenes* growth at different temperatures in heat-treated (blanched) vegetables, which has been converted to EGR_{5°C} using the square-root-based secondary model for bacterial growth. The intensity of the heat treatment ranged from 50° C for 60 s up to 90° C for 10 min. The mean, standard deviation and truncated maximum (mean + 2 standard deviations) of the growth rate was used for the mgQMRA (Table 2). The mean value was estimated to be $0.0117 \log_{10}/h$, meaning that, on average, after 10 h at 5° C the population increases by $0.117 \log_{10}$ units





- Decisions to make:
- 1) Assess the confidence on the compilation work done
- 2) Do we need to access the compiled data (source data)?
 - We opt for taking the distribution on EGR5 from the publication, as is

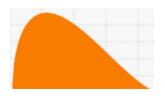


3) The stochastic function of growth Storage() for exposure assessment

Initial concentration

$$C_0 \sim xxx$$
 log CFU/g

Storage conditions



Hyperparameters and growth model

$$EGR_5 \sim Lognormal (-4.65, 0.63) \log/h$$

$$T_{min} = -1.18$$
 °C

$$MPD = 8 \log CFU/g$$

$$Growth = EGR_5 \left(\frac{Temp - T_{min}}{5 - T_{min}} \right) Time$$

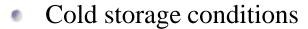
Output

$$C_f = \begin{cases} C_0 + Growth, & C_0 + Growth < MPD \\ MPD, & C_0 + Growth \ge MPD \end{cases}$$

4) Testing the function

Initial concentration (contaminated fraction)

$$C_0 \sim Normal(-0.5, 0.1) \log CFU/g$$



$$Time = 16 \text{ h}$$
 $Temp = 8 \text{ °C}$

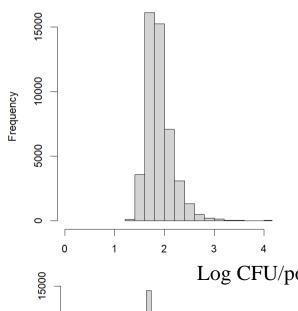
Initial concentration (contaminated fraction)

$$C_0 \sim Normal(-0.5, 0.1) \log CFU/g$$

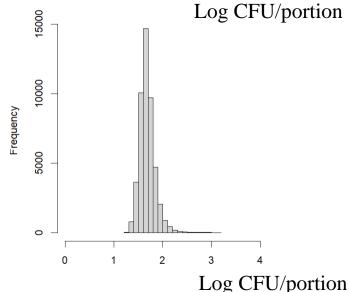
Heat treatment conditions

$$Time = 16 \text{ h}$$
 $Temp = 5 \text{ °C}$

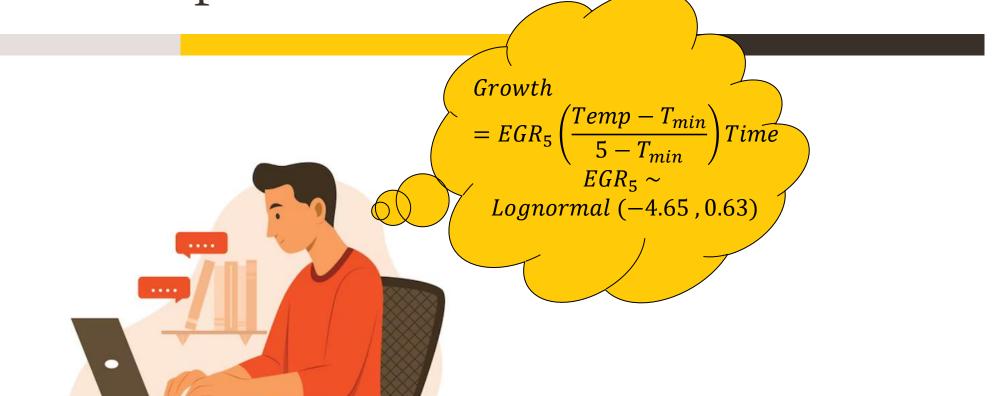




Outputs, Cf

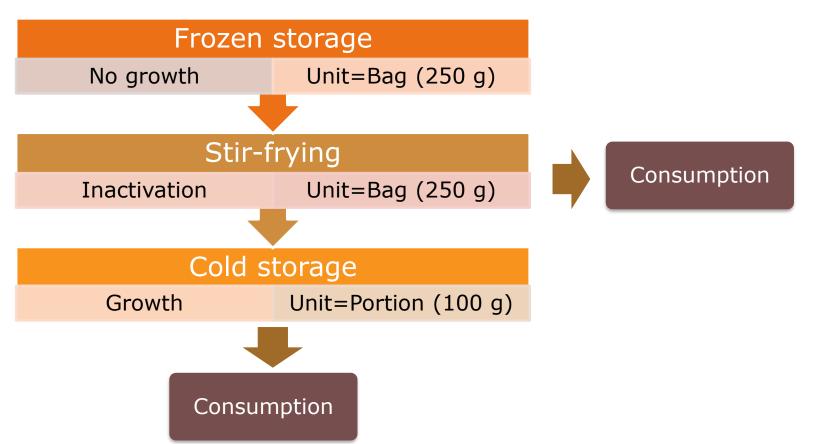


An example of use of growth/inactivation models in exposure assessment



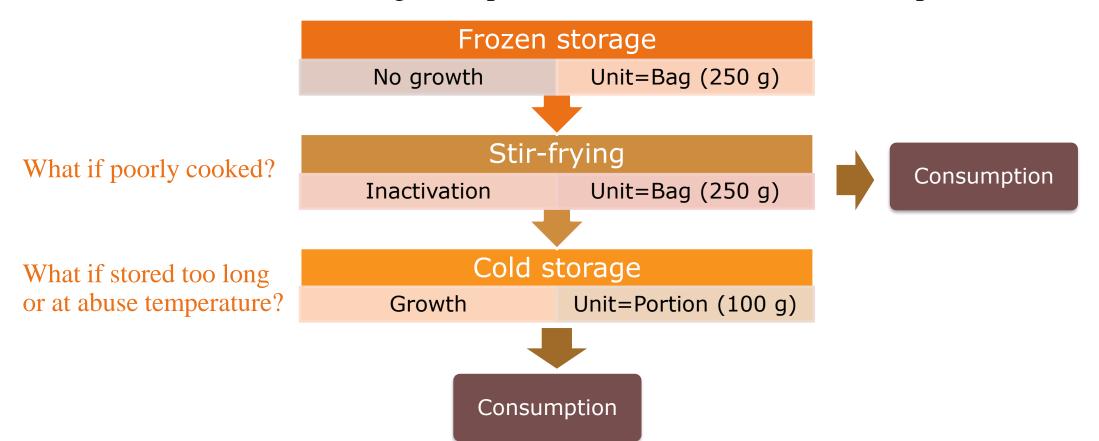
Example

• You wish to build a consumer-phase exposure assessment model of *L*. *monocytogenes* in frozen stir-fry vegetables to assess the impact of consumer's mishandling on exposure. Make a draft of the conceptual model



Example

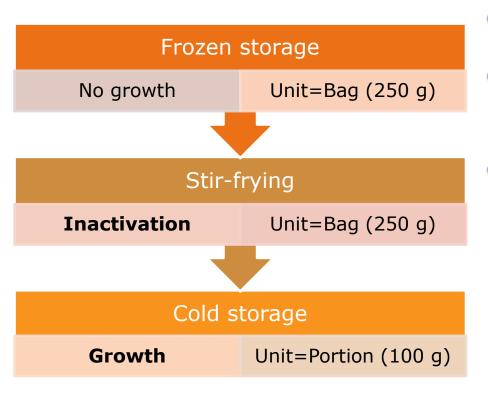
• You wish to build a consumer-phase exposure assessment model of *L*. *monocytogenes* in frozen stir-fry vegetables to assess the impact of consumer's mishandling on exposure. Make a draft of the conceptual model



Example

Data collection

Data pre-processing



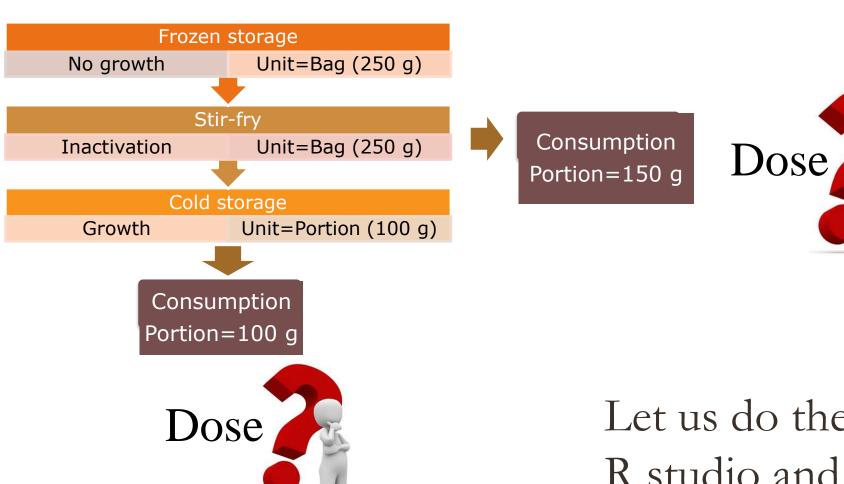
- C₀, Concentration of LM in stir-fry frozen vegs at retail
- P, Prevalence of contaminated packs
- Inactivation kinetics of LM in raw vegetables

Growth kinetics of LM in heat-treated (cooked) vegetables

• C_0 , Fitting distribution for C_0

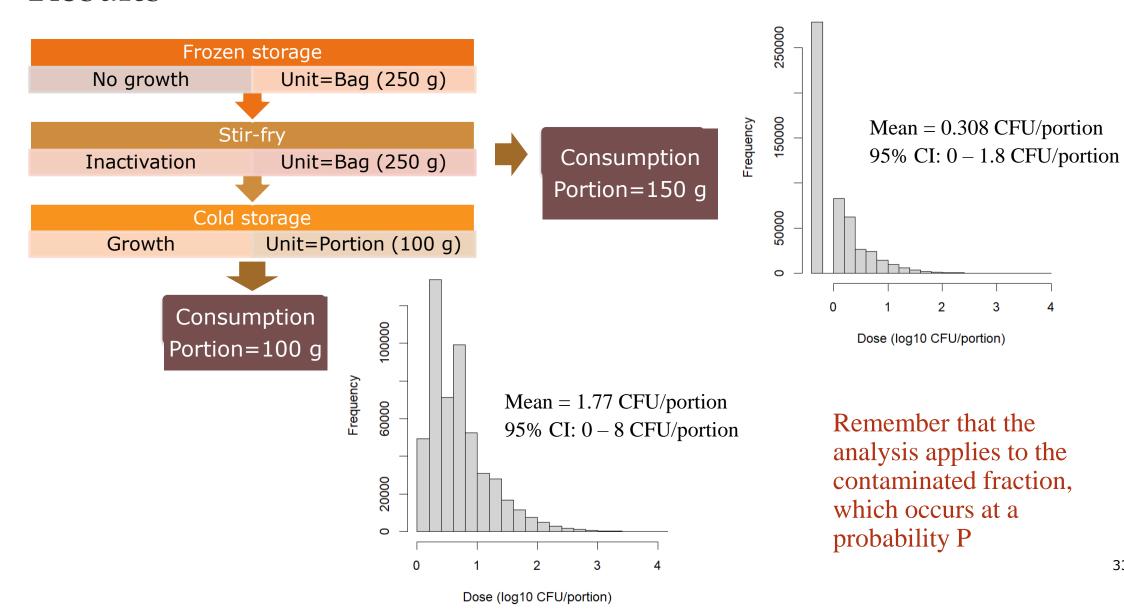
Building the function MildHeat()

Building the function Storage()



Let us do the job in R studio and estimate exposure

Results



Conclusions

- Knowing the pathogen's kinetics in the target food is a **key requisite** for conducting an exposure assessment
- The conceptual model is a very important step and is ultimately defined by the need for complexity (linked to decision making) and the amount of data available
- Different levels of data pre-processing may be needed when incorporating microbial kinetics into exposure assessments, which go from direct use of validated growth/inactivation parameters to the conduction of mixed-effects models from many published sources

Sources

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- Nauta, M. J. (2002). Modelling bacterial growth in quantitative microbiological risk assessment: is it possible? Int. J. Food Microbiol. 73: 297-304.
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 https://github.com/vcadavez/qraLm
- Tesson, V., Federighi, M., Cummins, E., Mota, J. O., Guillou, S., Bóué, G. (2020) A systematic review of beef meat quantitative microbial risk assessment models. Int J Environ Res Public Health, 21, 17(3):688. doi: 10.3390/ijerph17030688

Further reading

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