

## Uncertainty and variability in Bayesian inference for dietary risk: Listeria in RTE fish

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#### Listeria in Ready To Eat (RTE) Fish: Cold Smoked Salmon & Salt Cured Salmon, (CSS/SCS).

- (1) Concentration data & growth model
- (2) Consumption data
- (3) Bayesian inference
- (4) Dose-response model
- (5) Epidemiologic data: reported cases & population data, age groups.



#### (1) Variation between products $\mu_0$ + growth: $\mu_t$ = growth( $\mu_0$ ), t days



#### (2) Variation between consumptions: 48h food diaries



- Log-serving sizes ~ N( $\eta$ , $\delta^2$ ).
- Consumption on a day, given consumption on previous day:
  P(yes|yes)=p<sub>11</sub>. Likewise p<sub>00</sub>.
- Consumption on a day: two-state Markov chain stationary probability p<sub>1</sub>.

#### Each of the above have uncertain parameters:

• Core population parameters:  $\theta = (q, \mu, \sigma^2, \eta, \delta^2, p_{00}, p_{11})$ .

# (3) Bayesian inference: $P(\theta | data)$ uncertainty of population parameters

- Listeria prevalence in CSS/SCS (q)
  - Uncertain due to sample size, method accuracy.
- Concentration distribution: ( $\mu$ , $\sigma^2$ )
  - Uncertain due to sample size, and many values <LOQ.
- Serving size distribution: ( $\eta$ , $\delta^2$ )
  - Uncertain due to sample size, stratification by age.
- Consumption frequencies: transition probabilities (p<sub>00</sub>, p<sub>11</sub>)
  - Uncertain due to rare occasions, stratification by age.







#### (4) Conditional dose-response probability, given consumption of contaminated CSS/SCS & parameter r

•  $P(\text{illness} | \mathbf{r}, E(d)) = 1 - \exp(-\mathbf{r}E(d))$ 

$$\{d \sim \text{Poisson}(E(d))\}$$

- $E(d) = \exp(\mu_t^* + s^*) = \exp(q_t(\mu_0^*) + s^*)$
- $\mu_t^*$  = predicted log-concentration on day t,  $\mu_t^* = g_t(\mu_0^*)$ , predicted initial value  $\mu_0^*$ .
- $s^*$  = predicted log-consumption amount, if consuming.
- $\mu_0^*$ ,  $s^*$  predicted from the distributions:  $f(\mu_0^* | \mu, \sigma^2)$ ,  $f(s^* | \eta, \delta^2)$ , conditional on the uncertain  $\mu, \sigma^2, \eta, \delta^2$



#### (4) Conditional probability to acquire illness, allowing repeated consumptions

- Probability to start consuming, purchase of CSS/SCS.
- Probability to continue next day, same product.
- Chance of acquiring illness conditionally on 'still at risk' & exposure on a day.
- Total probability of illness, over several days, allowing repeated use:  $P(\text{illness} | \mathbf{r}, \theta) =$  $(1 - p_1)p_{01}q[P_1(\text{ill}|\mathbf{r},\mu,\sigma,\eta,\delta) + \sum_{t=2}^7 \prod_{i=1}^{t-1} (1 - P_i(\text{ill}|\mathbf{r},\mu,\sigma,\eta,\delta))p_{11}^{t-1}P_t(\text{ill}|\mathbf{r},\mu,\sigma,\eta,\delta)]$ 
  - 25

• (Age group specific).



# (4) Population illness probability (risk), individual variability integrated

- Accounting for individual variability in  $\mu_t^*$ ,  $s^*$  requires integration:
- $P_t(\text{illness } | \mathbf{r}, \mu, \sigma, \eta, \delta) = E(P_t(\text{illness } | \mathbf{r}, g_t(\mu_0^*), s^*)) =$  $\iint_{-\infty, -\infty}^{\infty, \infty} (1 - \exp(-\mathbf{r} \exp(g_t(\mu_0^*) + s^*))) f(\mu_0^* | \mu, \sigma) f(s^* | \eta, \delta) d\mu_0^* ds^*$
- This may have no analytic solution, but a Monte Carlo approximation:
- $\hat{P}_t(\text{illness} | \mathbf{r}, \mu, \sigma, \eta, \delta) \approx \sum_{k=1}^{K} (1 \exp(-\mathbf{r} \exp(g_t(\mu_0^{*k}) + s^{*k})))/K$ where  $\mu_0^{*k}, s^{*k}$  are sampled from  $f(\mu_0^* | \mu, \sigma)$  and  $f(s^* | \eta, \delta)$ .

#### (5) Epidemiologic data



- Unknown dose-response parameter **r** for specific age groups.
  - Uncertain due to lack of detailed epidemiological data, stratification by age.
- Using the reported cases as epidemiological data in the model.
  - Proportion of cases due to CSS/SCS?  $0 \le \text{cases}_{age} \le \text{total}_{age}$ .
  - Could use source attribution modelling, expert opinion, scenario assumption.
    - Reported cases around **12** in both 65-74 and 25-64 year olds, annually.
    - Population sizes about **470,000** vs **2,900,000**.
    - So we know *something* about incidence.  $\rightarrow$  Use this in the model.
  - Actually, published estimates of r rely on some back-calculations, or 'adjusting' predictions with reported incidence.

## (5) Full model Bayesian inference



• Full posterior density from the model, all parameters  $r, \theta$ , formally:

 $P(r, \theta | \text{concentration & consumption data, cases, popula}) \propto \hat{P}(\text{cases} | r, \theta, \text{popula}) P(\text{concentration & consumption data} | \theta) P(r, \theta)$ 

- Where  $\hat{P}(cases|r, \theta, popula)=Poisson()$  is based on Monte Carlo approximation of the population risk within each MCMC iteration.
  - Intractable likelihood function.
  - Also denoted "2D" Monte Carlo, or MC within MCMC.
  - Increases computational burden.





### **Unquantified uncertainty**

- Growth model with fixed parameters?
  - No home storage data.
  - Assumed temperatures as scenarios.
- Unevenly distributed, clustered microbes, mixing?
  - No data.
- Variable susceptibility among consumers?
  - Can only relate exposure and incidence data by main age-groups.
- Unknown size of purchased packages?
  - Total number of servings?
- Majority of consumptions were at home, but not all.
- Not all cases due to CSS/SCS, although major risk. Source attribution, under reporting.



#### Quantify as much uncertainty & variability as you can!

(while keeping it simple, feasible, evidence based...)

• This was easy  $\rightarrow$ 

- This was possible  $\rightarrow$
- It gets harder here  $\rightarrow$
- ... ... Uhhhh  $\rightarrow$



← but some of these *could still be* important.



# Thank you!

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