

Tracking uncertainties in mechanistic models *for risk assessment of pest control strategies*

Virgile BAUDROT

CBGP – 24 septembre 2019

PhD 2013-2016



Post-Doc 2016-2018



Post-Doc 2018-2020



Modélisation des interactions trophiques impliquant des transferts de contaminants biologiques (*E. multilocularis*) et chimiques (ETMs)

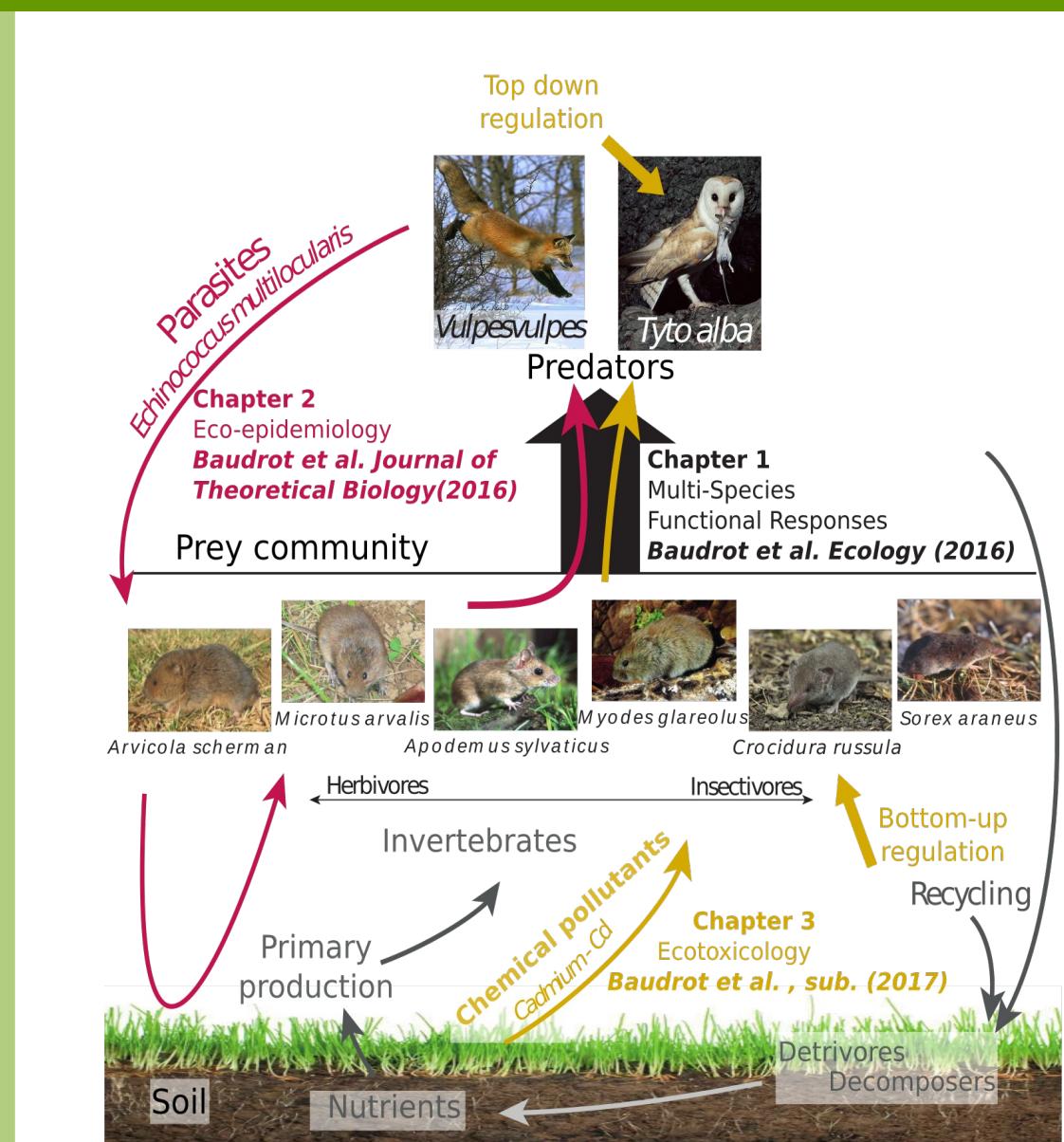
Director:

Francis Raoul

Co-supervisors:

Clémentine Fritsch,

Antoine Perasso

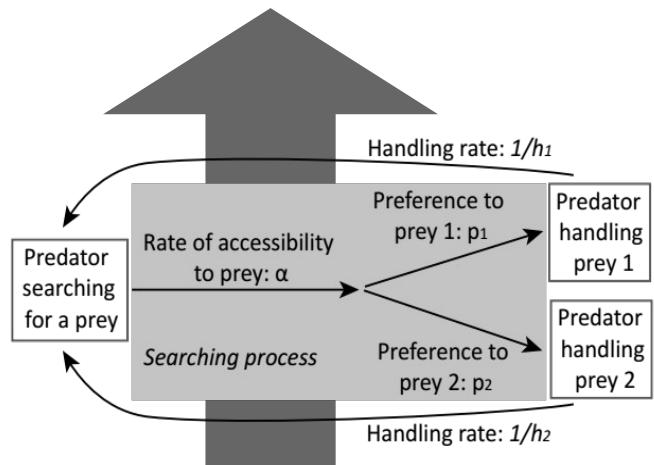




Vulpes vulpes



Tyto alba



Arvicola scherman



Microtus arvalis

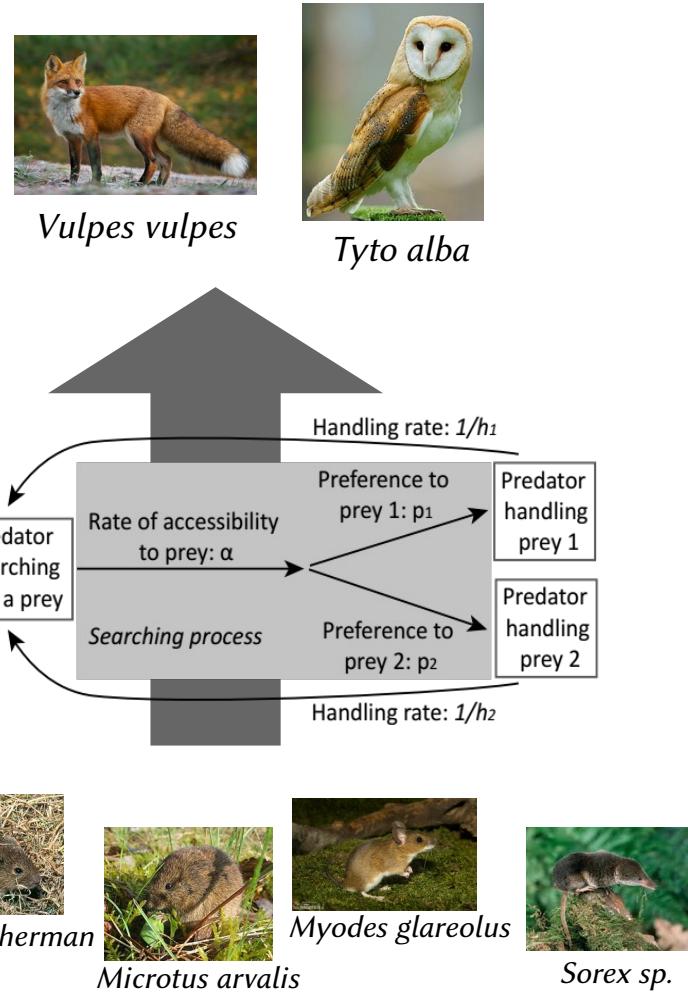


Myodes glareolus



Sorex sp.

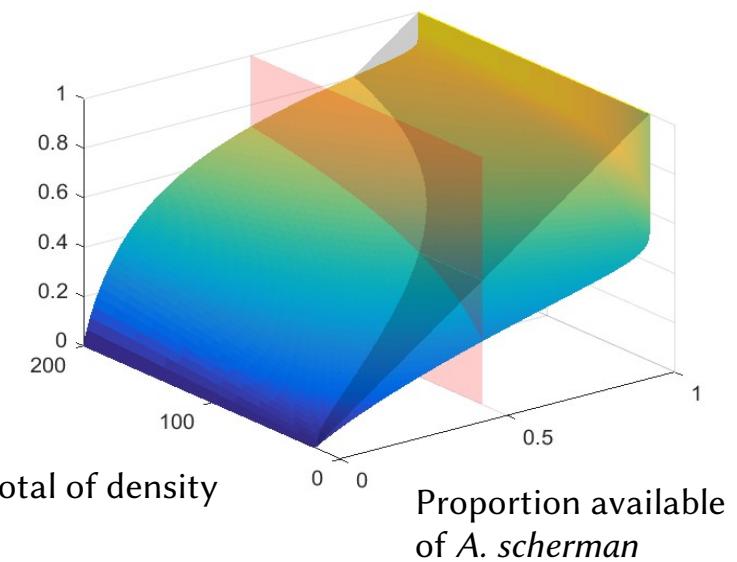
$$\Phi_i(\vec{x}) = p_i(\vec{x}) \times \frac{\alpha(\vec{x})}{1+h\alpha(\vec{x})} = [p_i(\vec{x})] \times \Theta(\vec{x})$$



Prey switching ...
... density dependent
... frequency dependent

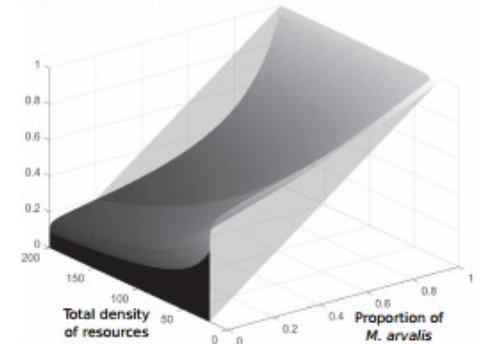
$$\Phi_i(\vec{x}) = p_i(\vec{x}) \times \frac{\alpha(\vec{x})}{1+h\alpha(\vec{x})} = [p_i(\vec{x})] \times \Theta(\vec{x})$$

Prop. *A. scherman* ingested / *V. vulpes*

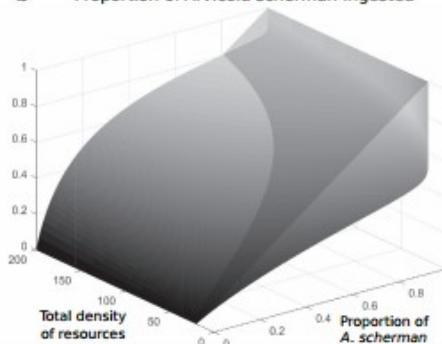




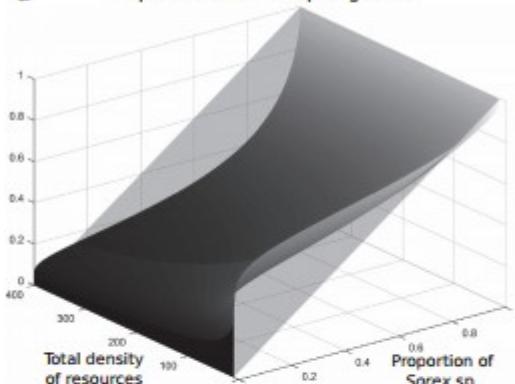
a Proportion of *Microtus arvalis* ingested



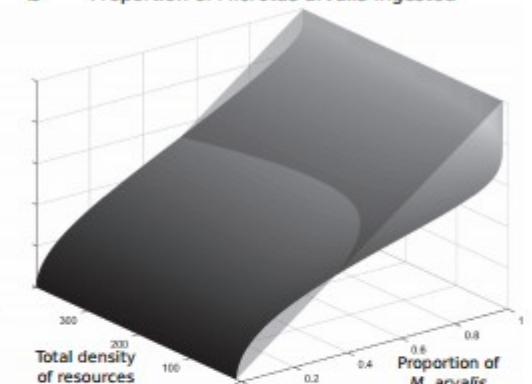
b Proportion of *Arvicola scherman* ingested



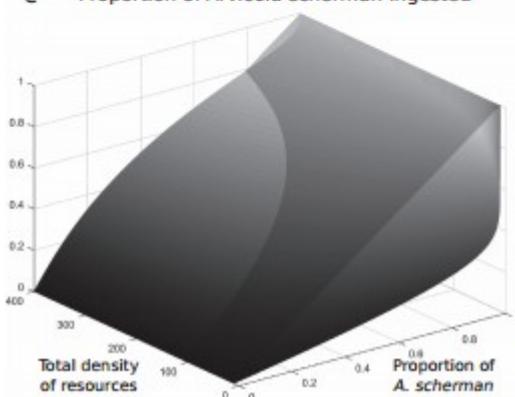
a Proportion of *Sorex sp.* ingested



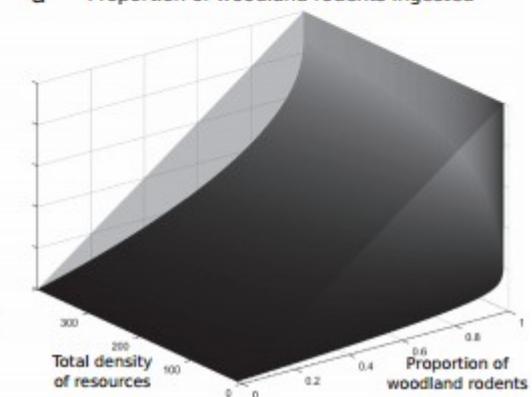
b Proportion of *Microtus arvalis* ingested

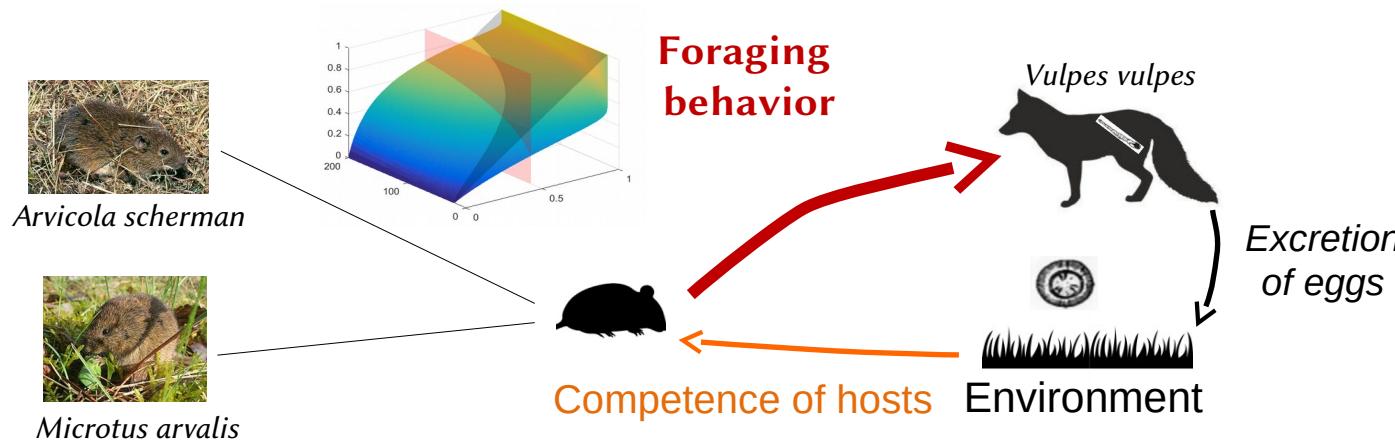


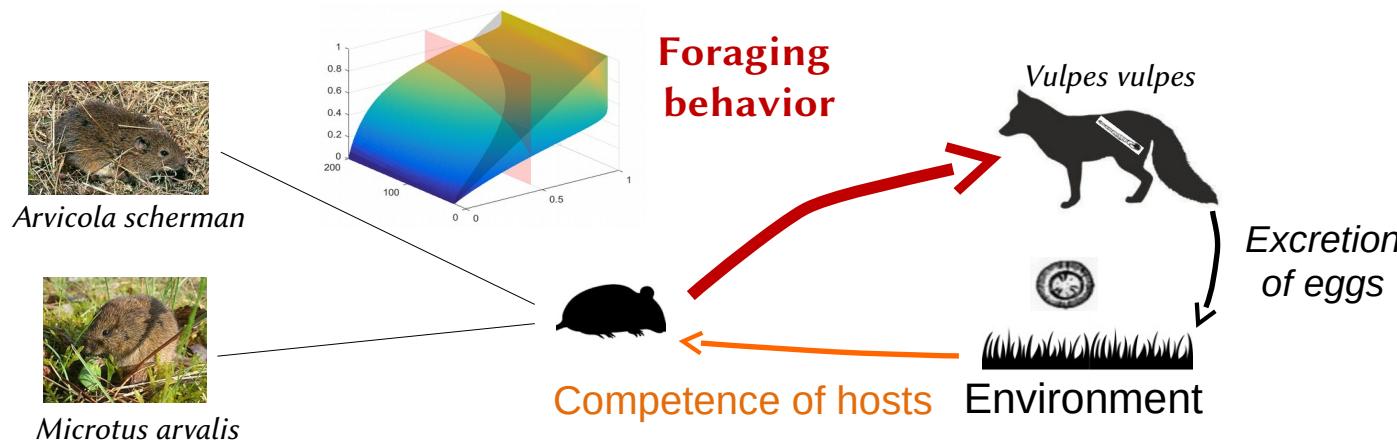
c Proportion of *Arvicola scherman* ingested



d Proportion of woodland rodents ingested





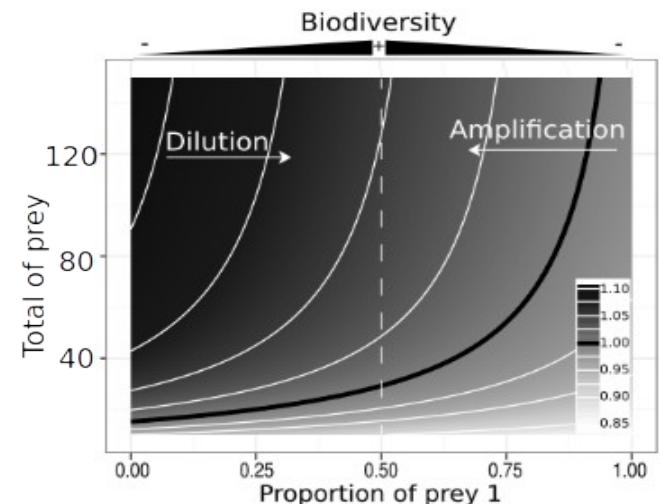


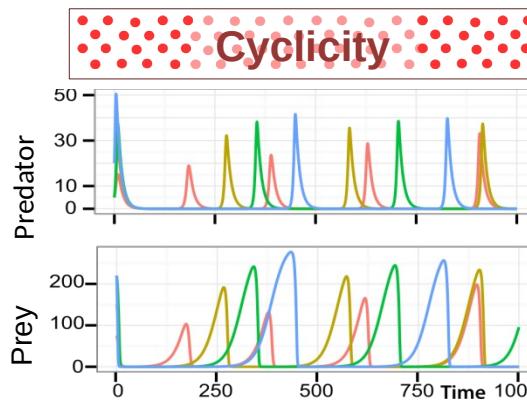
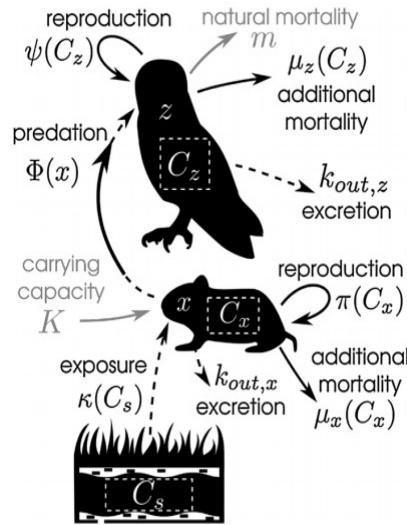
Basic reproductive number

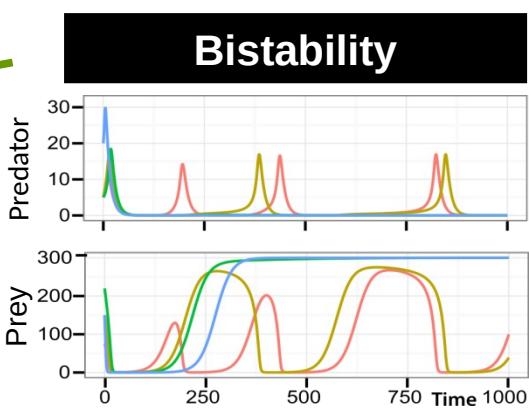
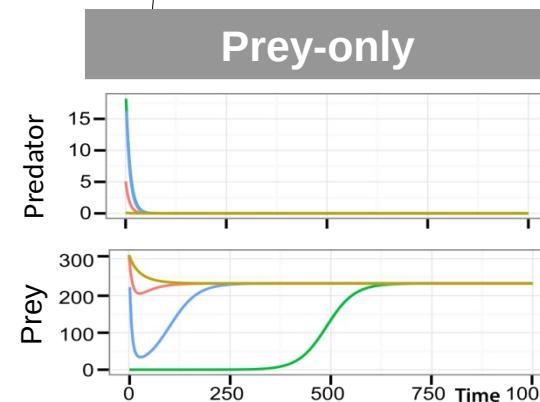
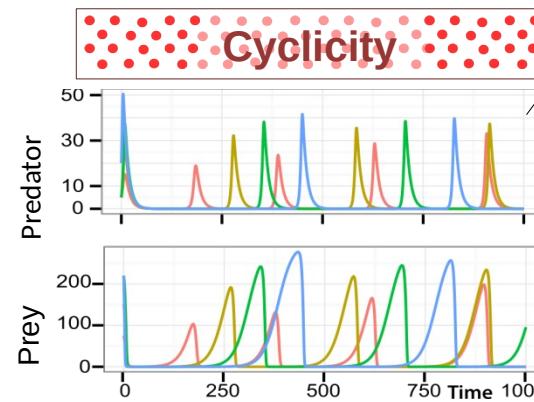
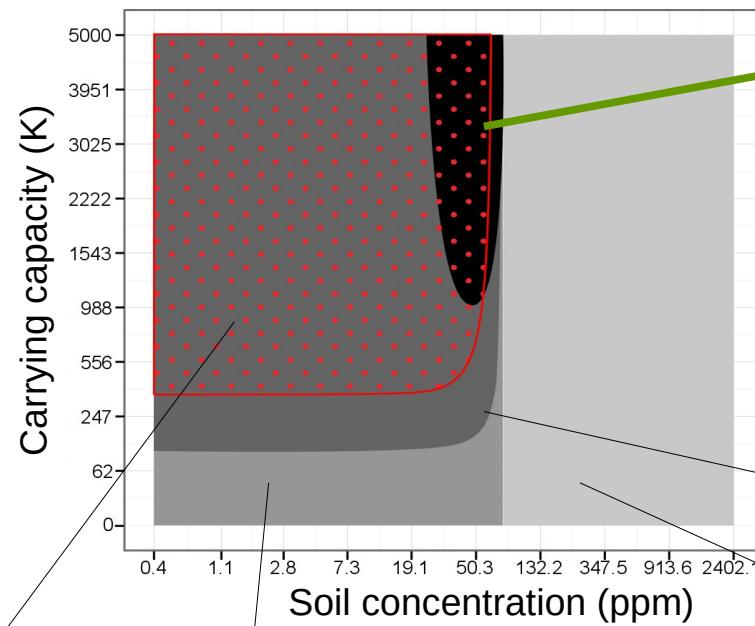
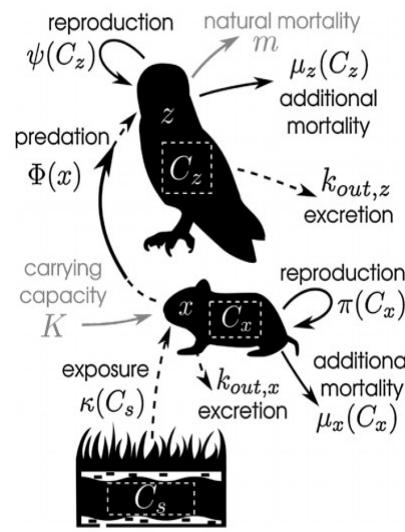
$$\mathcal{R}_0 = \sqrt{\frac{\eta z^*}{b(b_z + \mu)} \times (\Gamma_1 \Phi_1(x_1^*, x_2^*) + \Gamma_2 \Phi_2(x_1^*, x_2^*))}$$

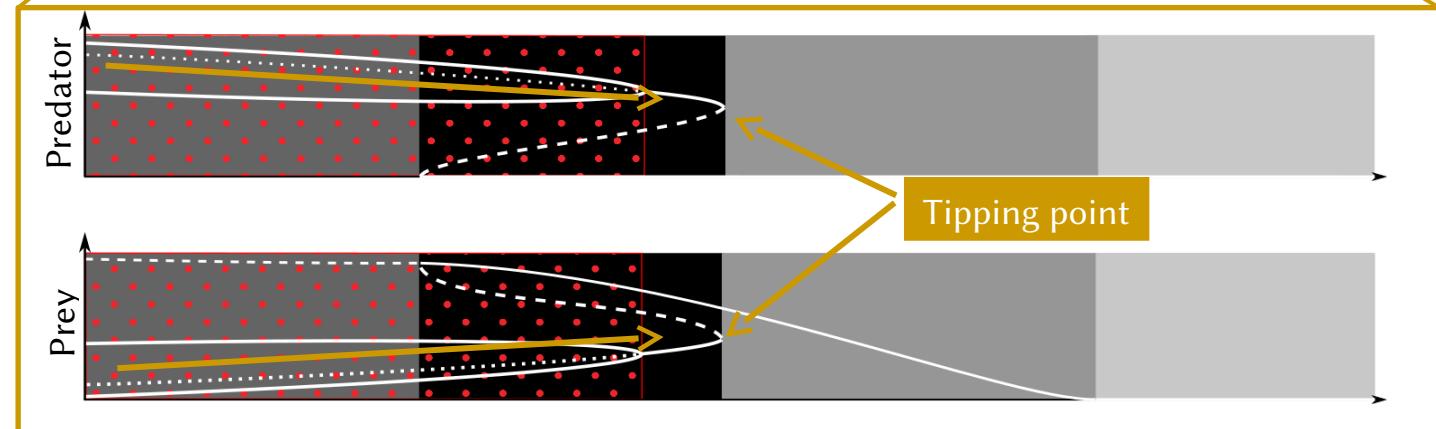
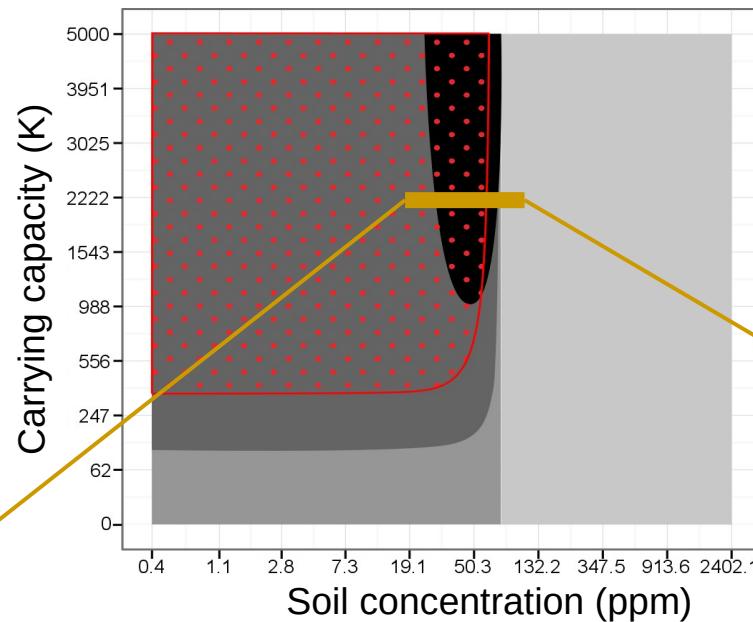
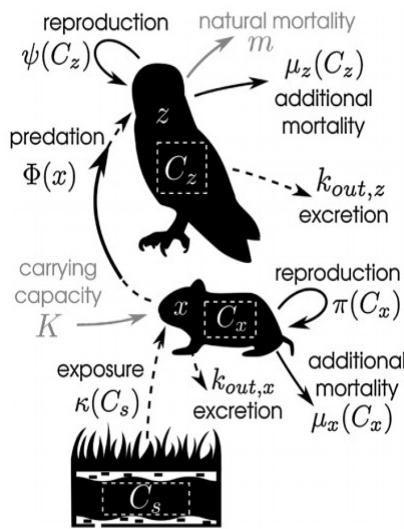
“Introduction” of susceptibles Competence of hosts

hosts diversity & disease risk



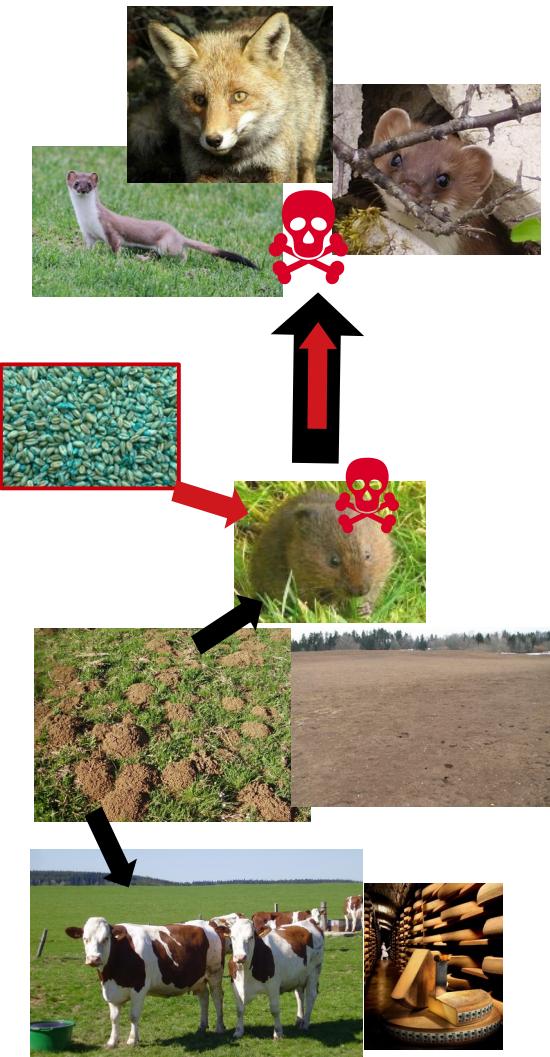


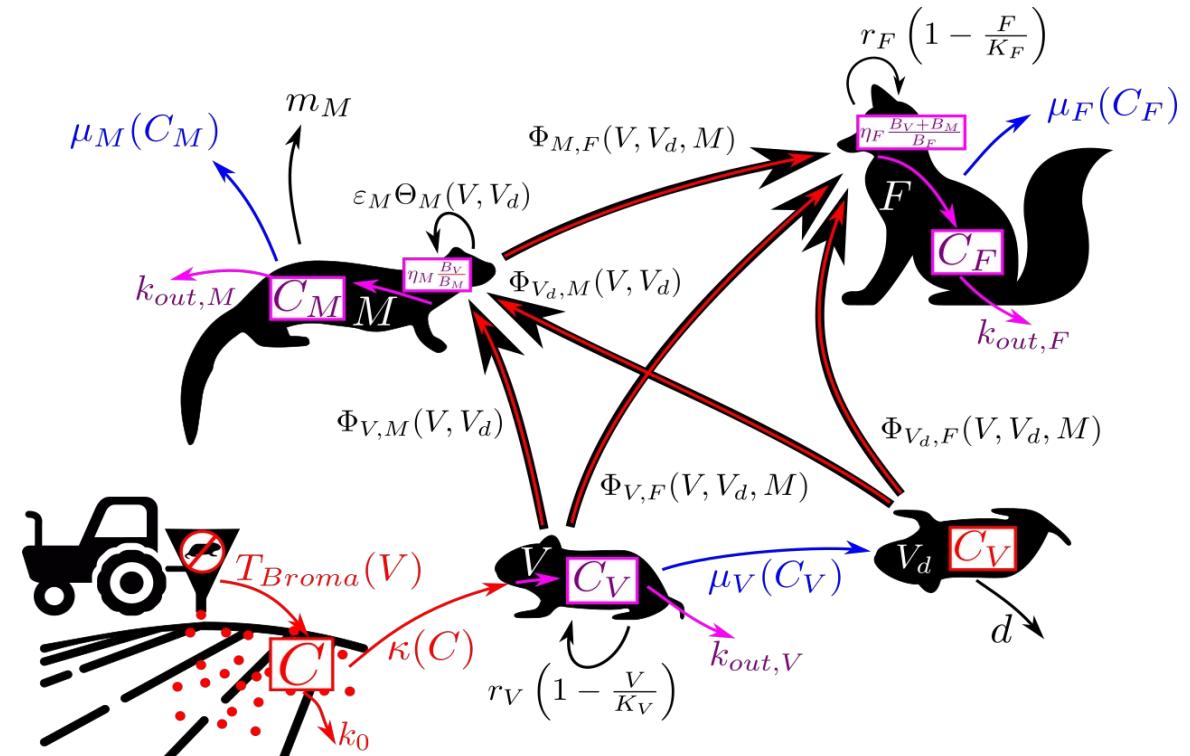
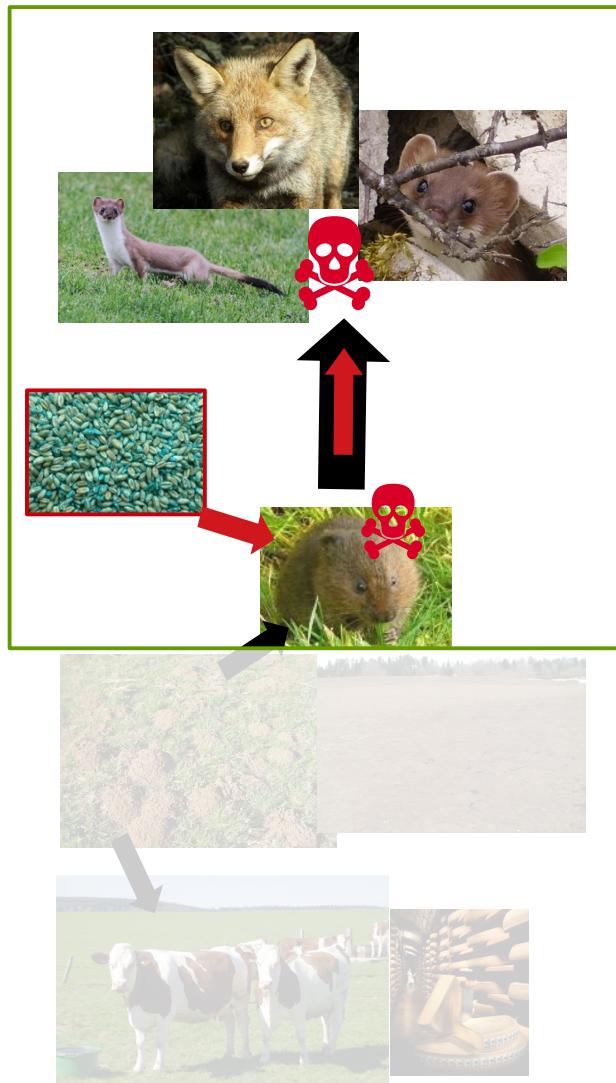


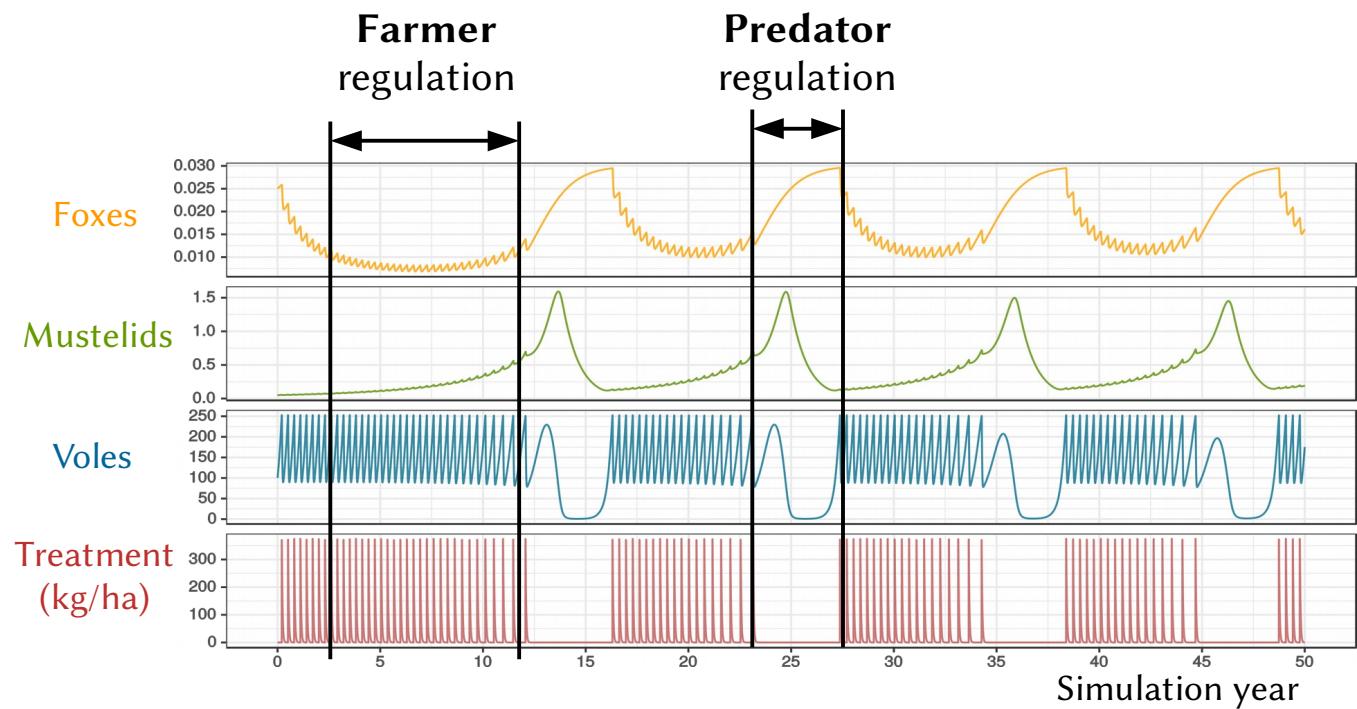
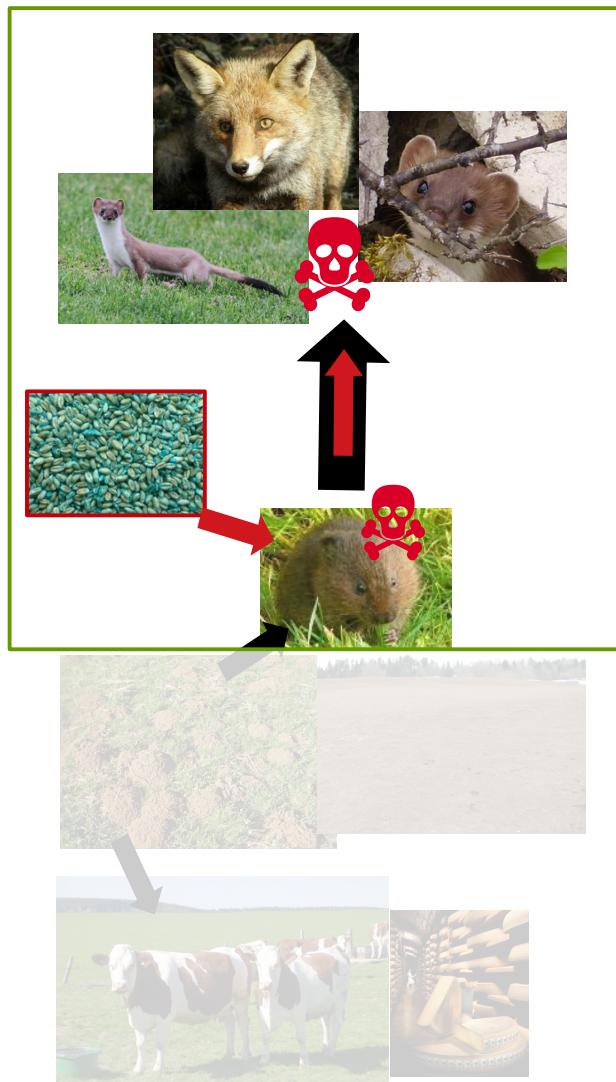


From observation of simple system, tipping point are hardly predictable...

... so in real complex !







→ **Buffer in time to maintain biocontrol**

Implementation of Bayesian inference for TKTD models
A way to track the propagation of uncertainties in environmental risk assessment

Virgile BAUDROT
Sandrine CHARLES



“In biology, variability is the main invariant”

Guiseppe Longo & Francis Bailly (2006)

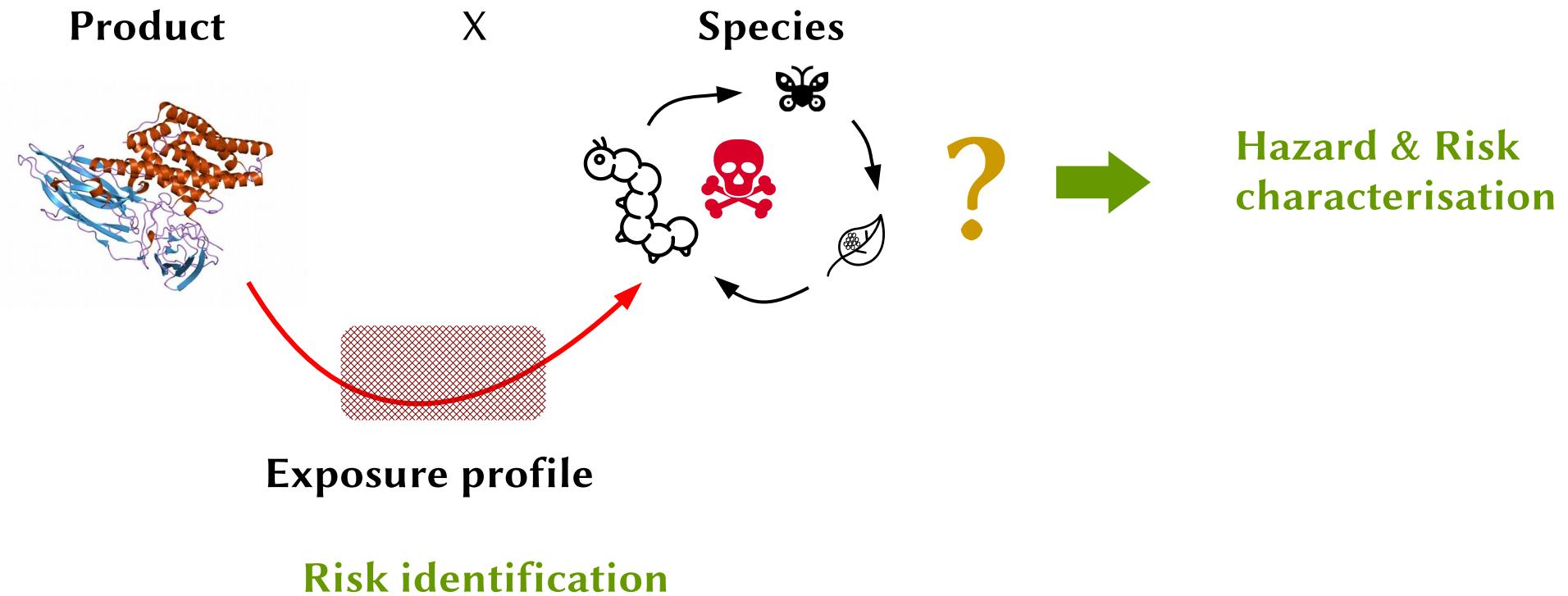
Mathématiques et sciences de la nature ; la singularité physique du vivant

Mechanistic models

→ **Challenge theories**

→ **Application?**

Hazard identification



Hazard identification

Product x Species

**Data**

$$\mathcal{D} = \{\mathcal{E}, \mathbf{N}\}$$

- experimental design
- observation (survivors)

Calibration

$$\text{Likelihood } \pi(\mathcal{D}|\theta)$$

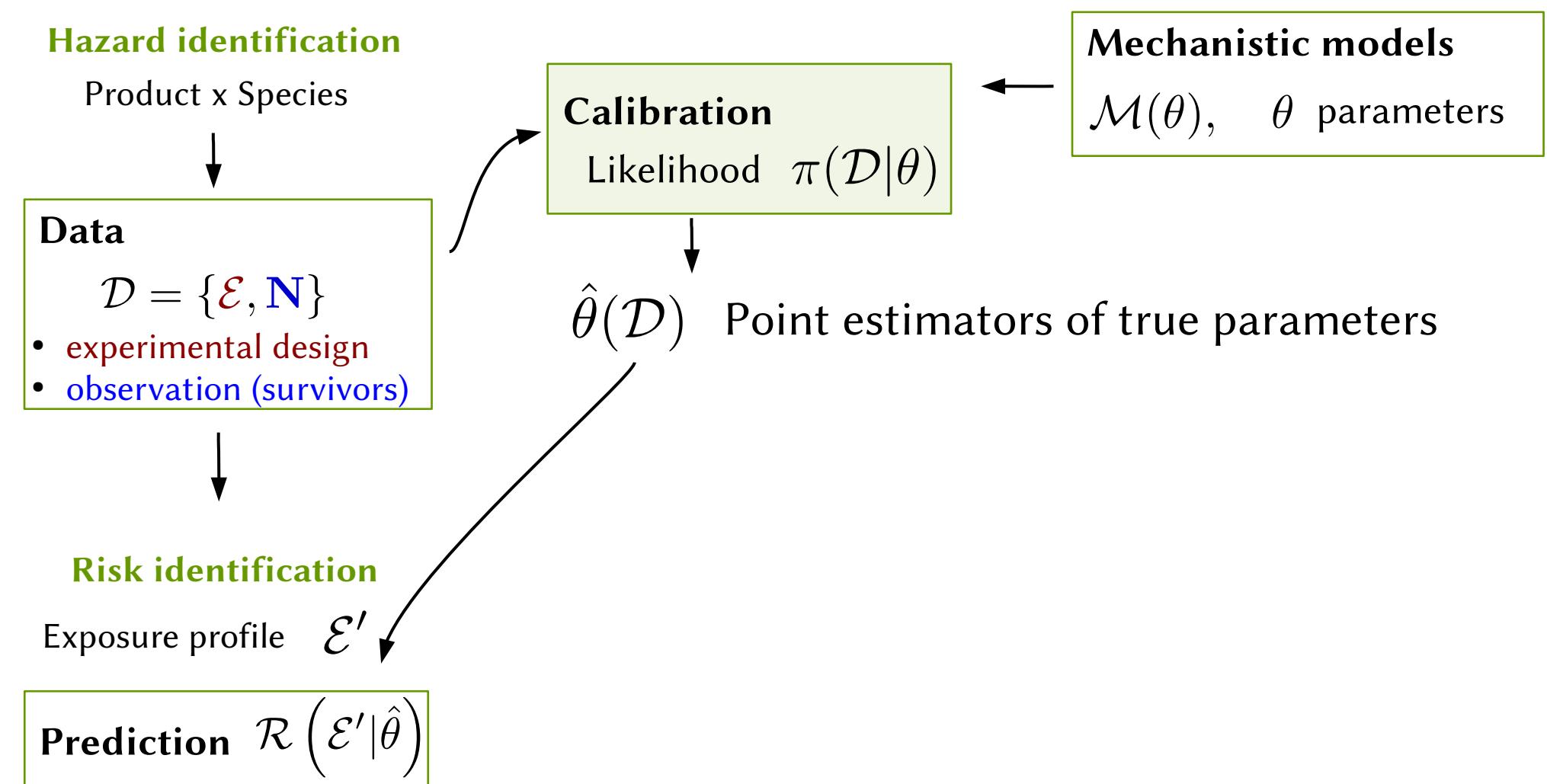
Mechanistic models

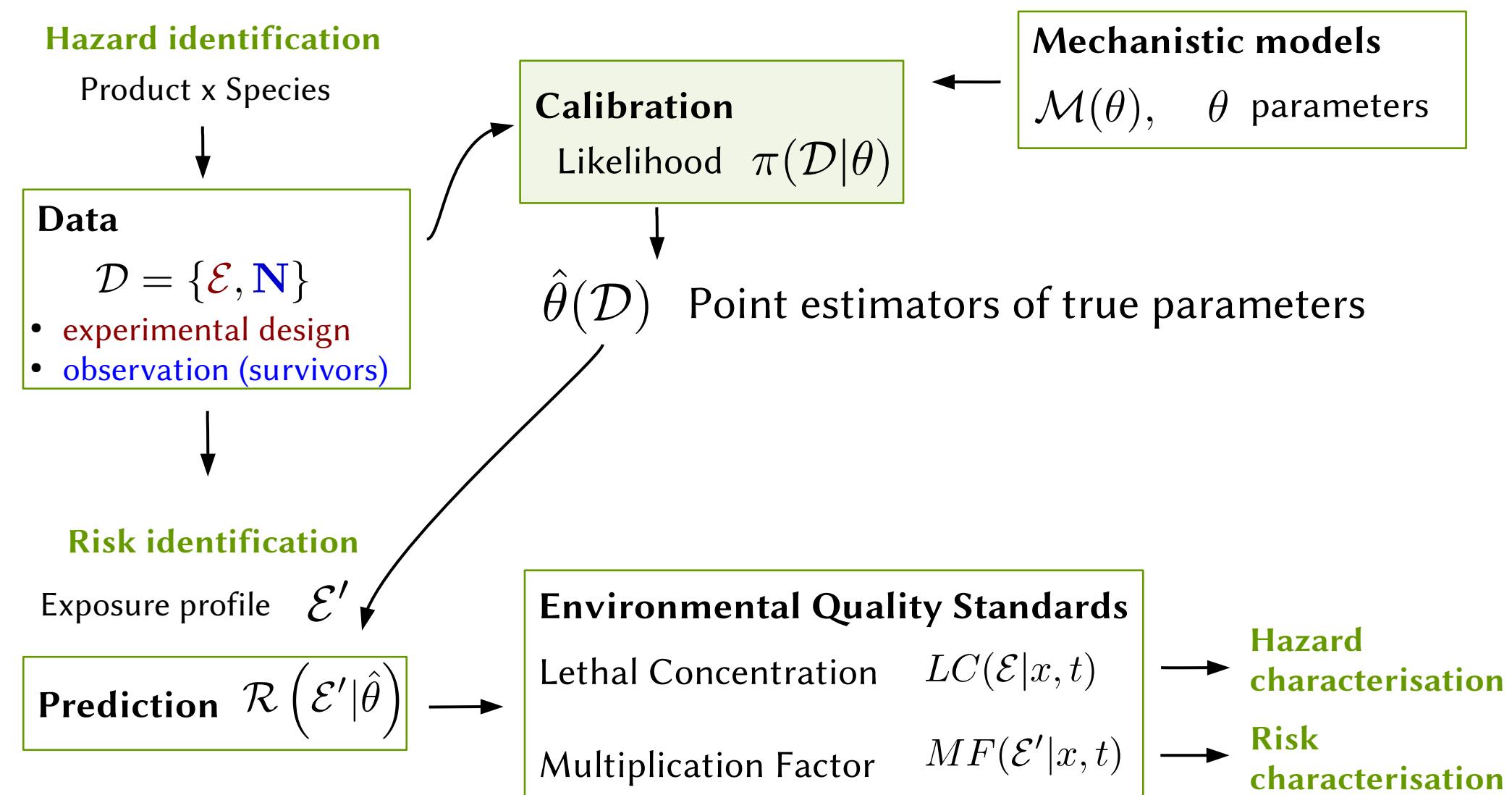
$$\mathcal{M}(\theta), \quad \theta \text{ parameters}$$

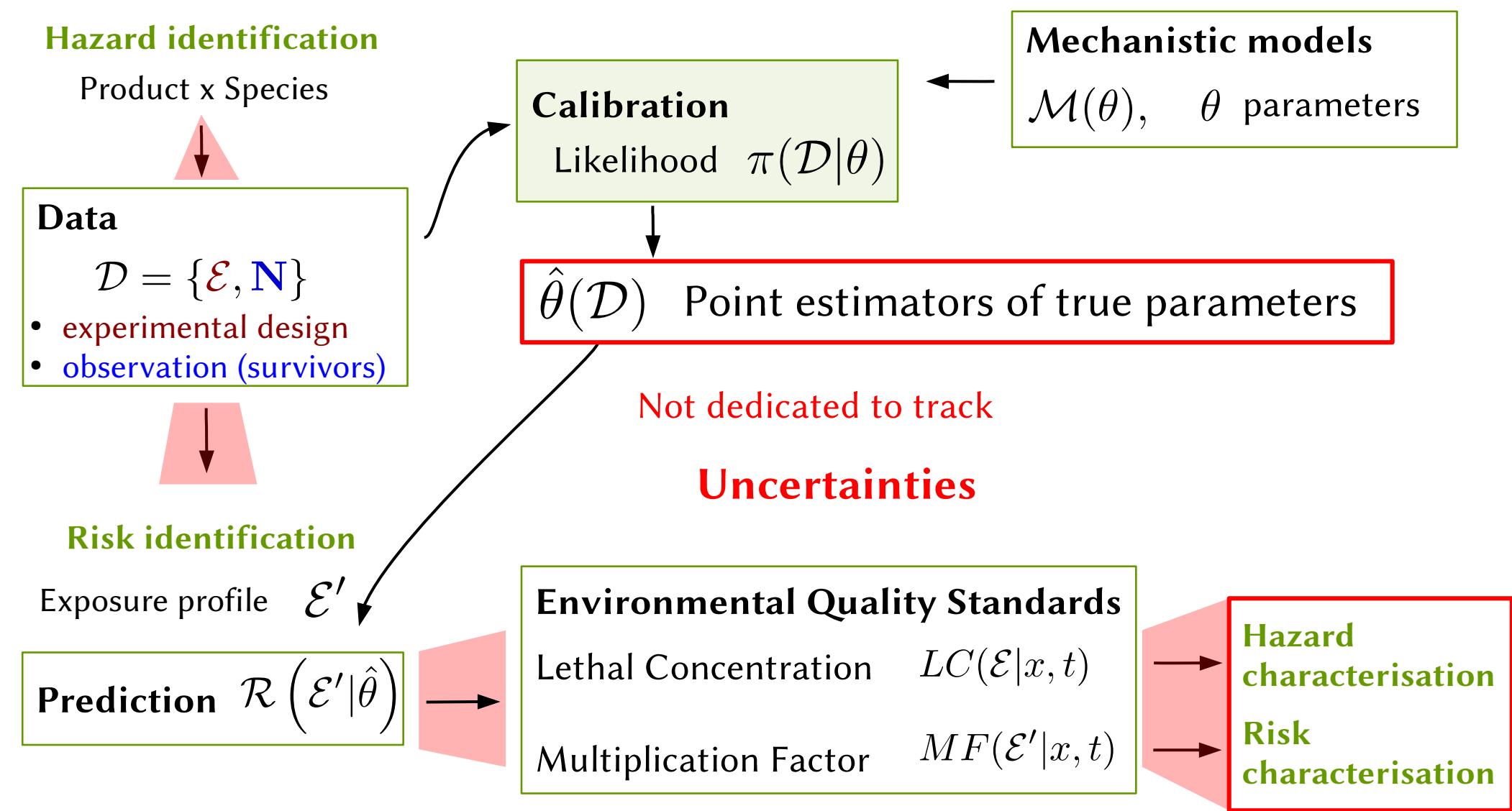


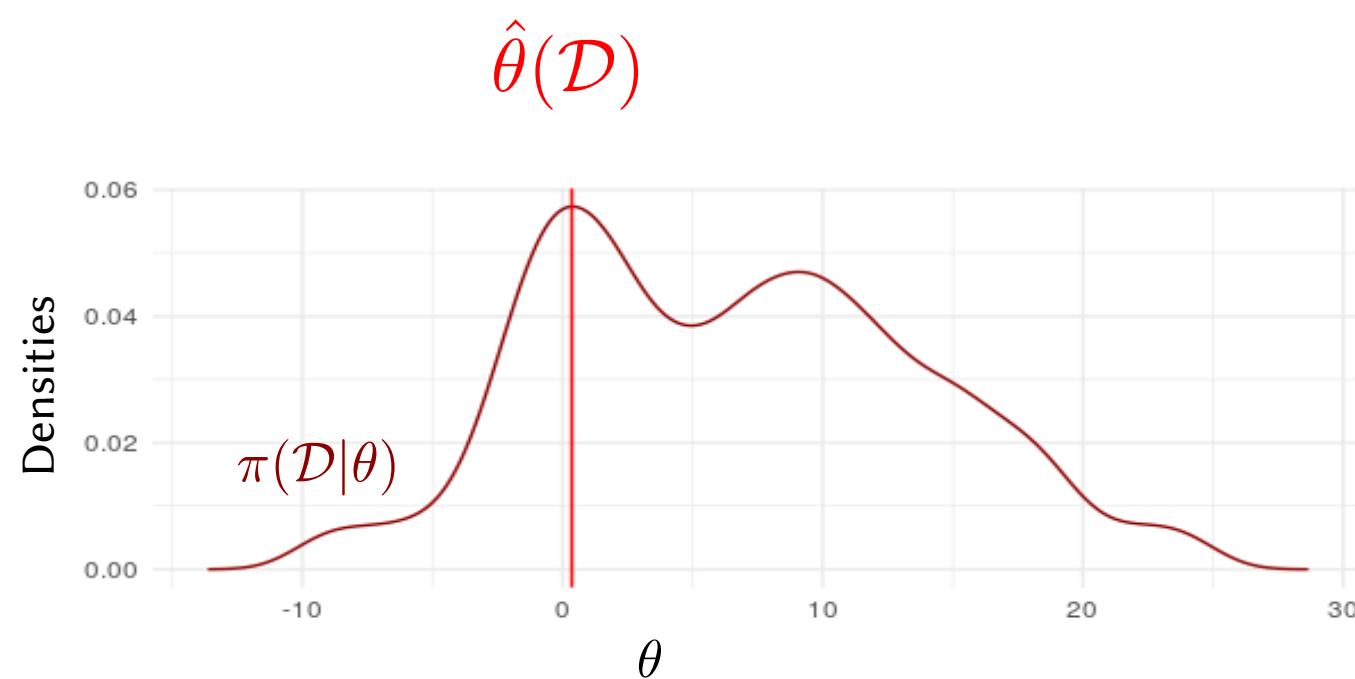
$$\hat{\theta}(\mathcal{D})$$

Point estimators of true parameters





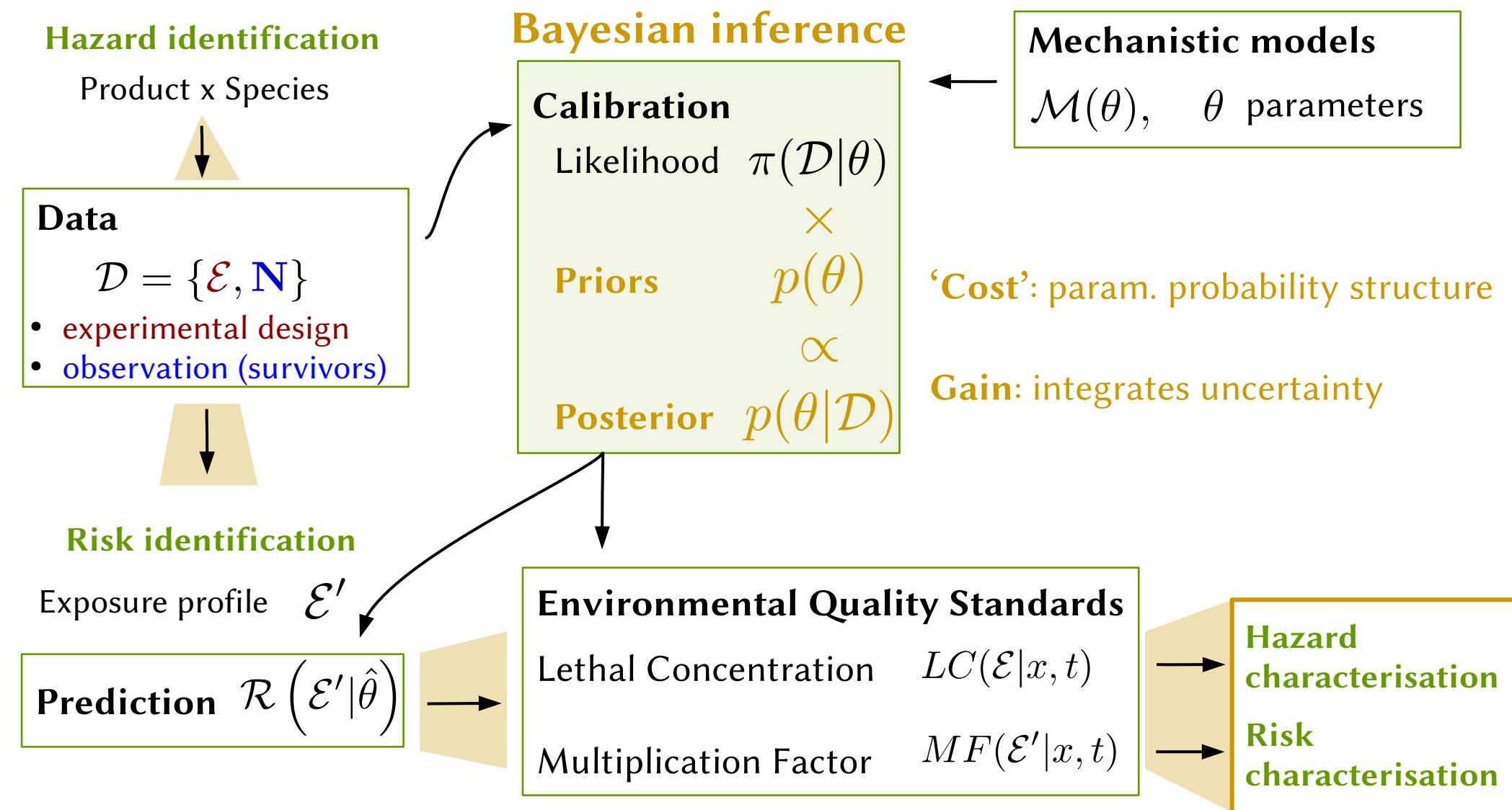


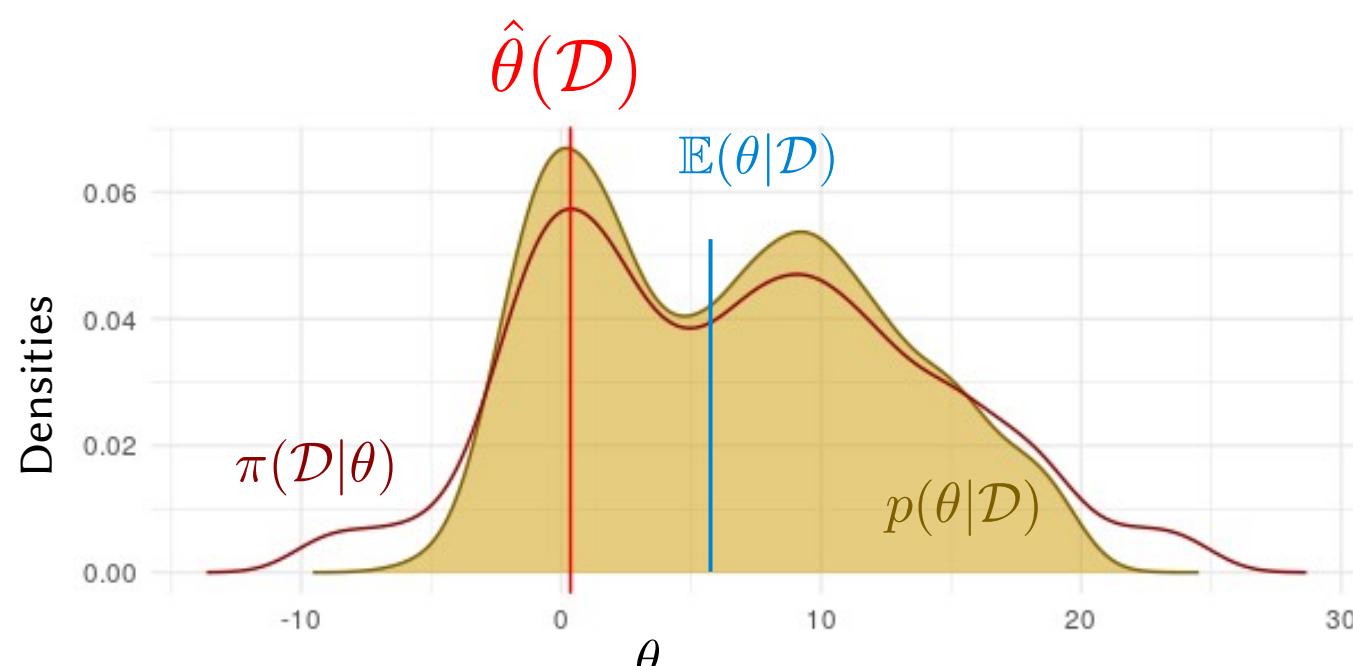


Frequentist

➡ max likelihood

$$\hat{\theta}(\mathcal{D}) = \underset{\theta}{\operatorname{argmax}} \pi(\mathcal{D}|\theta)$$





Frequentist

➡ max likelihood

$$\hat{\theta}(\mathcal{D}) = \underset{\theta}{\operatorname{argmax}} \pi(\mathcal{D}|\theta)$$

Bayesian

$$p(\theta|\mathcal{D}) \propto \pi(\mathcal{D}|\theta) \times p(\theta)$$

➡ probability structure on the parameter space

Toxicokinetic

$$\frac{dD_{surv}(t)}{dt} = k_d (C_{ext}(t) - D_{surv}(t))$$

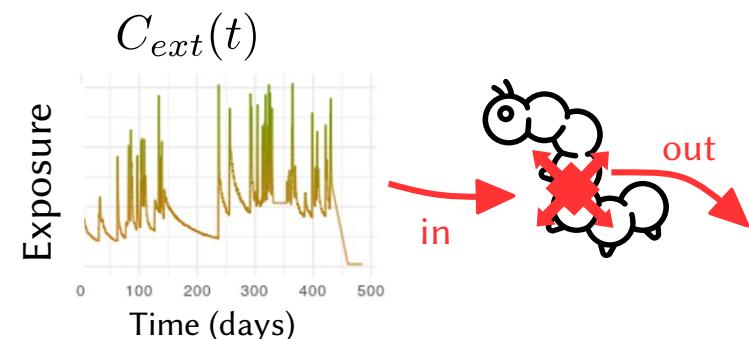
Toxicodynamic

$$h(t) = h_+ \max_{0 \leq \tau \leq t} (D_{surv}(\tau) - z, 0) + h_b$$

$$S_{SD}(t) = \exp \left(- \int_0^t h(\tau) d\tau \right)$$

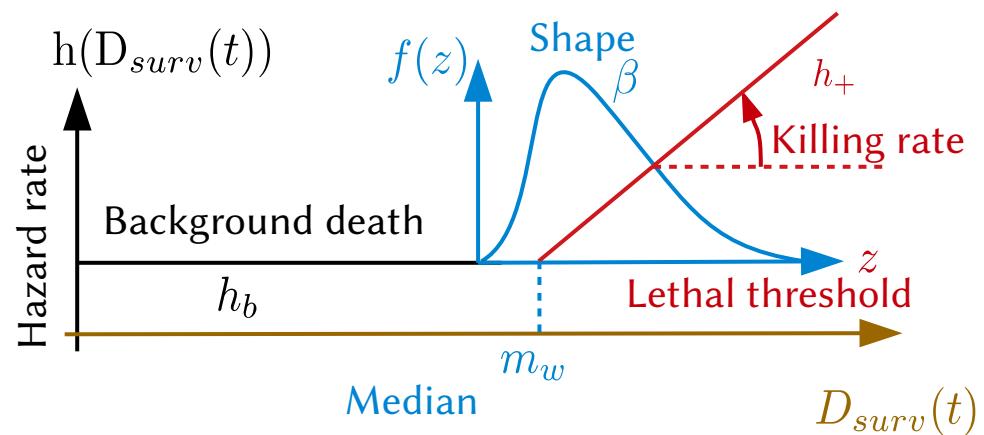
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Toxicokinetic

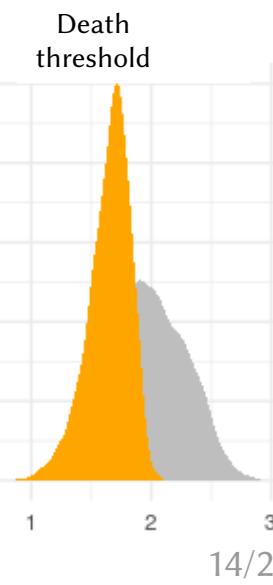
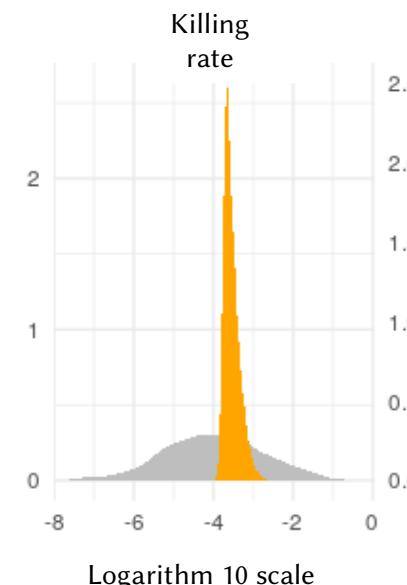
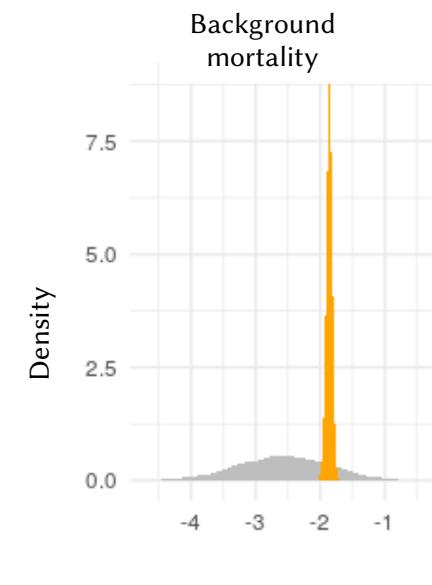
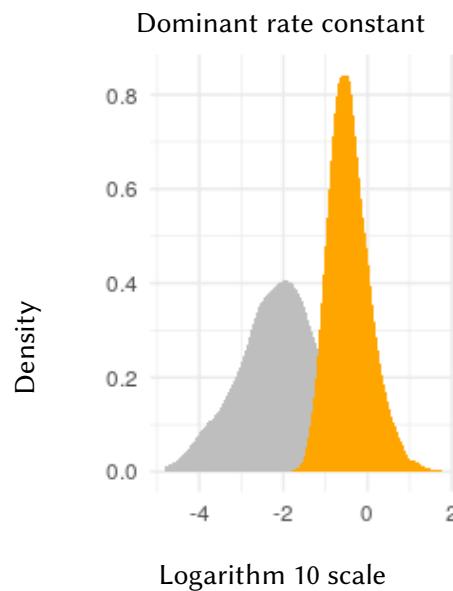
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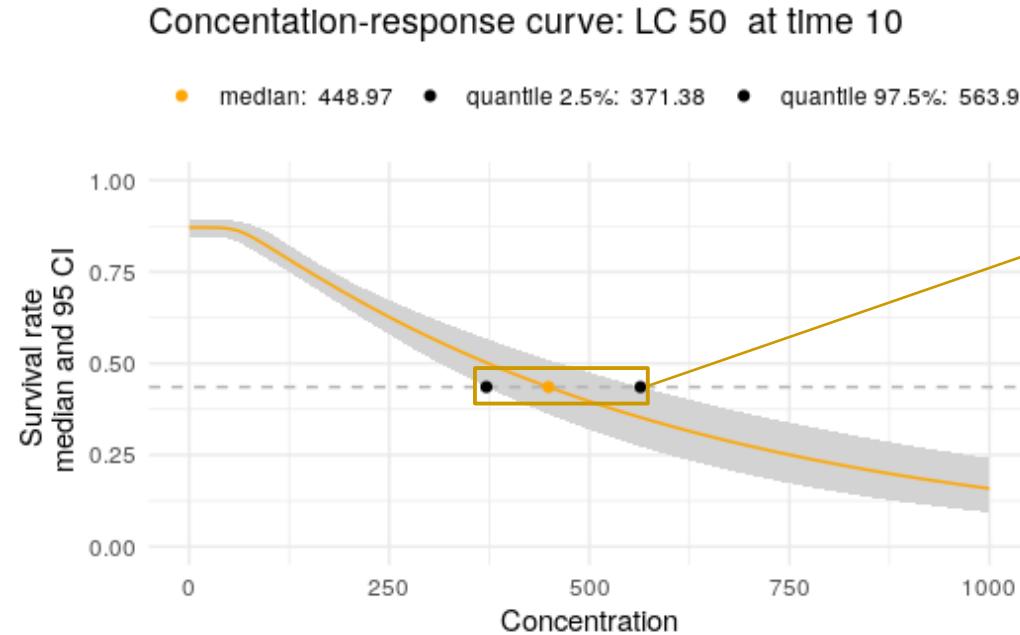
$$S_{SD}(t) = \exp \left(- \int_0^t h(\tau) d\tau \right)$$

Bayesian inference $\pi(\mathcal{D}|\theta) \times p(\theta) \propto p(\theta|\mathcal{D})$



→ Uncertainties around Environmental Quality Standard

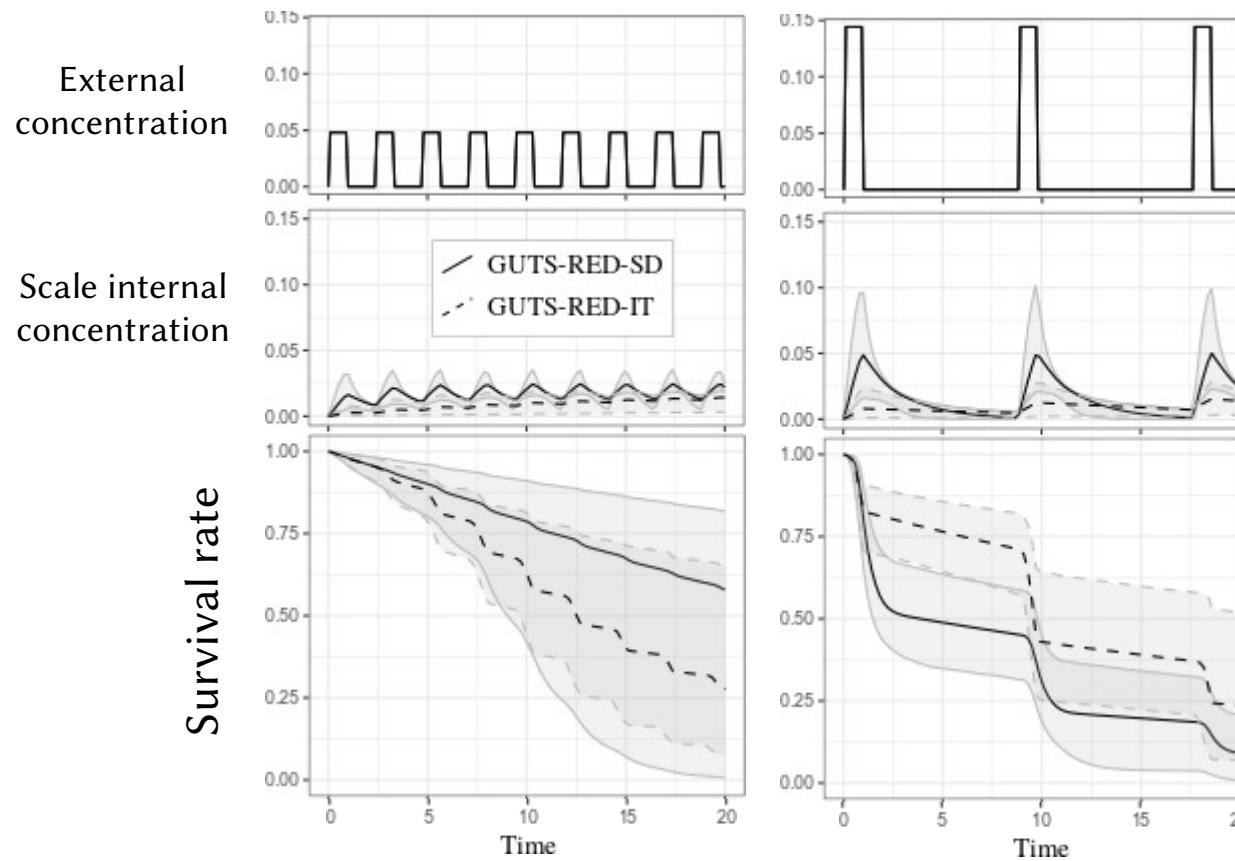
$LC(\mathcal{E}|x, t)$



Baudrot, V. ; Preux, S. ; Ducrot, V. ; Pavé, A. and Charles, S. (2018) *New insights to compare and choose TKTD models for survival based on an inter-laboratory study for Lymnaea stagnalis exposed to Cd.* Env, Science & Tech. 52(3) 1582-1590.

Baudrot, V. and Charles, S. (2019) *Recommendations to address uncertainties in environmental risk assessment using toxicokinetic-toxicodynamic models.* PCI Ecology (2018) => Scientific Reports. 9(11432)

→ Uncertainties propagation over new exposure profiles

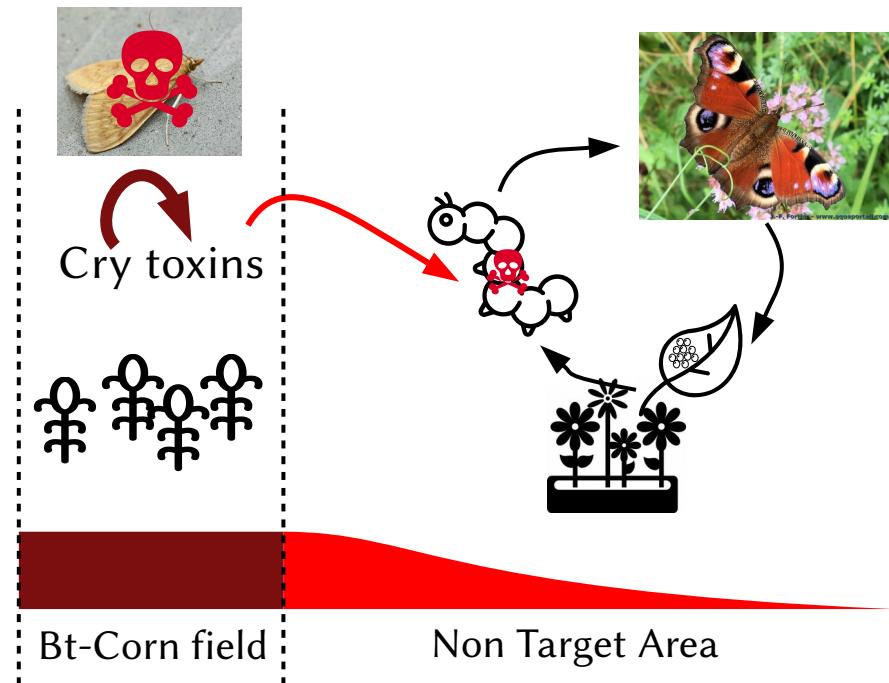


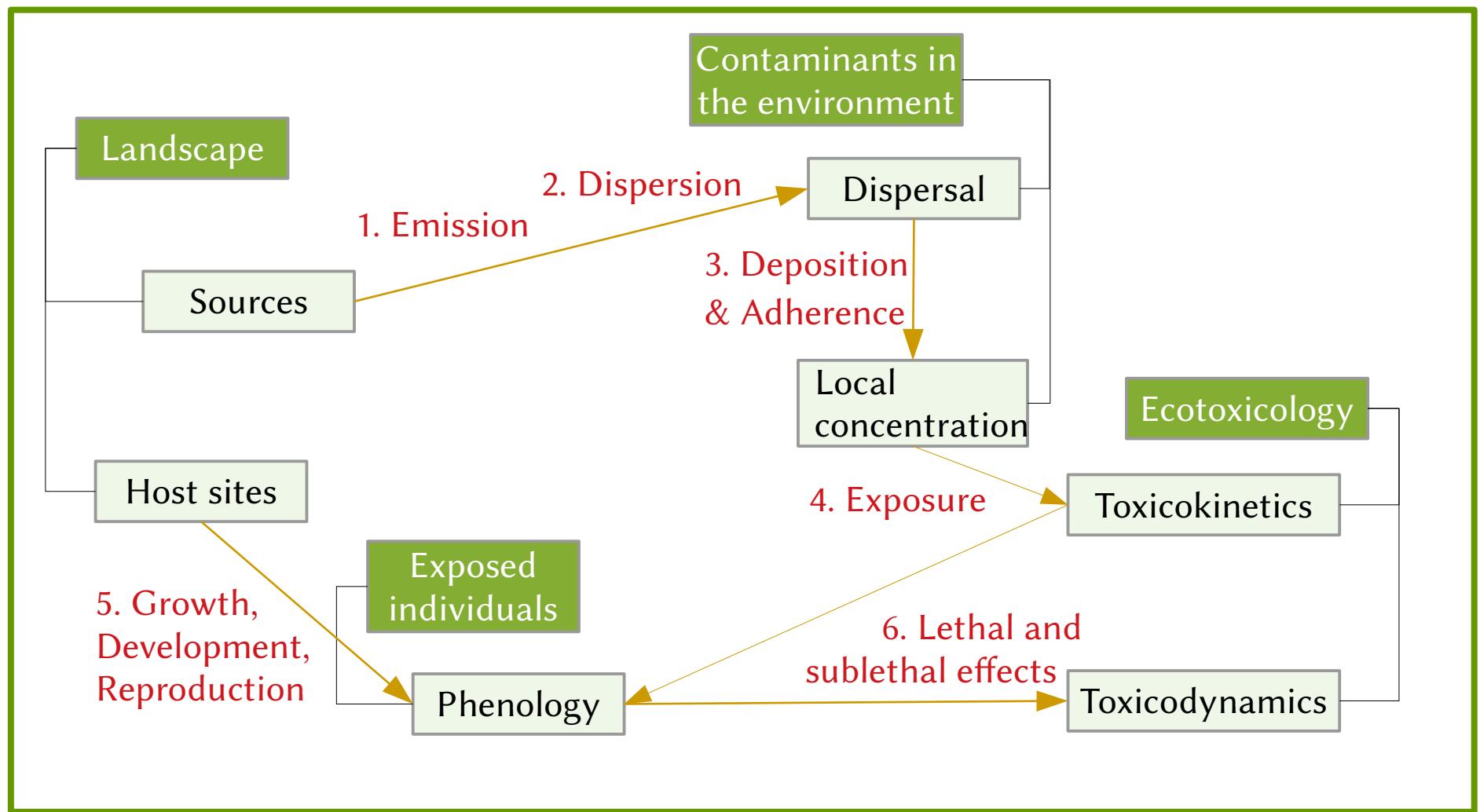
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BriskaR - A spatio-temporal exposure-hazard model for assessing environmental risk of Bt-maize on Non-Target Lepidoptera

Virgile BAUDROT
Samuel SOUBEYRAND
Antoine MESSÉAN
Andreas LANG
Stefanescu CONSTANTI





Mechanistic models $\mathcal{M}(\theta)$
parameters θ

Data $\mathcal{D} = \{\mathcal{E}, \mathcal{O}\}$
experiment \mathcal{E} ; observations \mathcal{O}

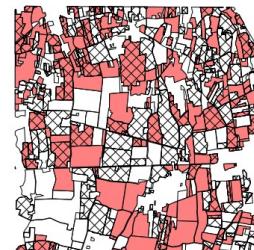
1. Emission

Fields: C_n

Spatio-temporal emission:

$$\tilde{E}(x, t) = \sum_{n \in N} \mathbf{1}(x \in C_n) E_n(t)$$

■ GM Fields

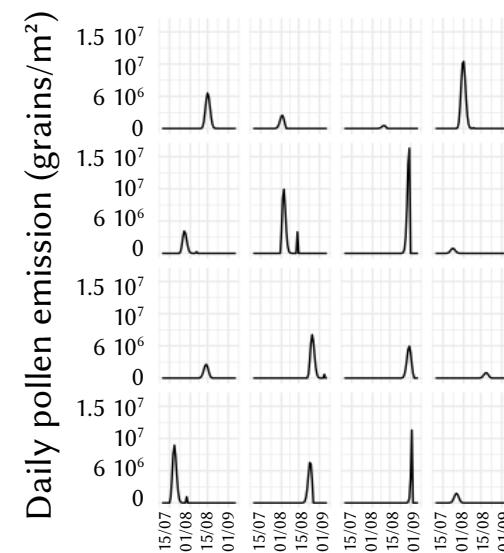


2. Dispersion

Dispersal kernel: $K(x, t)$

Contaminant intensity:

$$\lambda^{disp}(y, t) = \int_{\Omega} \tilde{E}(x, t) K(y - x) dx$$



Mechanistic models $\mathcal{M}(\theta)$
parameters θ

Data $\mathcal{D} = \{\mathcal{E}, \mathcal{O}\}$
experiment \mathcal{E} ; observations \mathcal{O}

Prediction $\mathcal{R}(\mathcal{E}'|\hat{\theta}(\mathcal{D}))$
environment \mathcal{E}' ; inference params. $\hat{\theta}(\mathcal{D})$

1. Emission

Fields: C_n

Spatio-temporal emission:

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GM Fields



Convolution computed with
Fast Fourier Transform

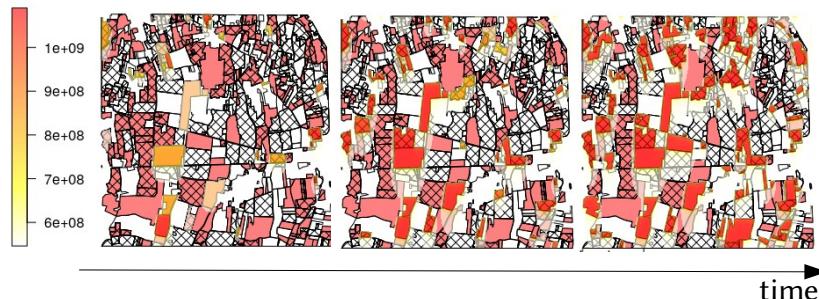
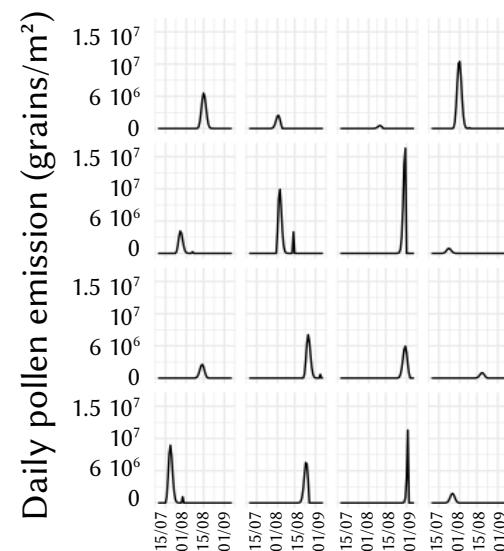
$$\tilde{E} \otimes K(y, t) = \mathcal{F}^{-1} \left(\mathcal{F}(\tilde{E}) \mathcal{F}(K) \right)$$

2. Dispersion

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Mechanistic models $\mathcal{M}(\theta)$
parameters θ

3. Deposition & Adherence

$$\lambda_{local}(y, t) = (1 - \alpha(Z(t))) \lambda_{local}(y, t - 1) + \beta \lambda_{disp}(y, t)$$

4. Exposure

5. Development

$$\delta_0(T) = \exp(\rho T) - \exp\left(\rho T_{max} - \frac{T_{max}-T}{\Delta}\right) + \lambda$$

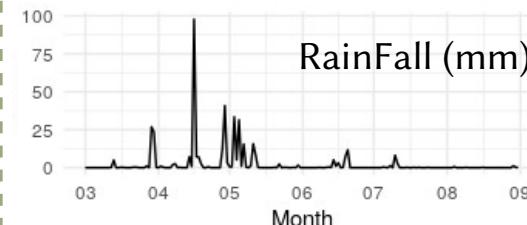
- $r(T)$: development rate
- T: temperature
- T_{max} : upper survival temperature
- ρ, Δ, λ : other parameters to fit

Mechanistic models $\mathcal{M}(\theta)$
parameters θ

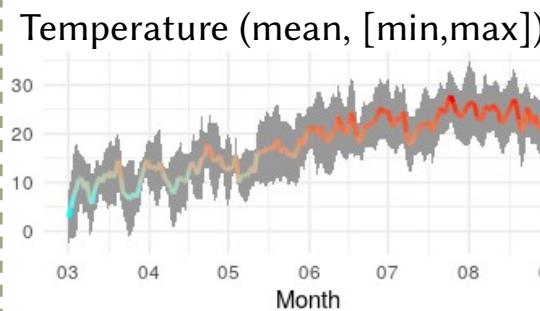
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experiment \mathcal{E} ; observations \mathcal{O}

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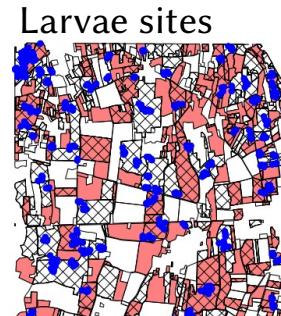
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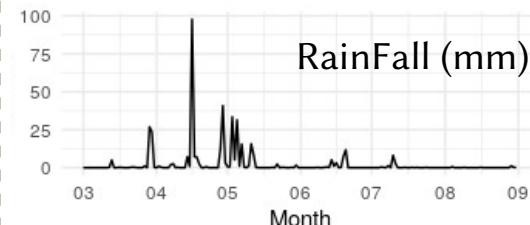
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environment \mathcal{E}' ; inference params. $\hat{\theta}(\mathcal{D})$

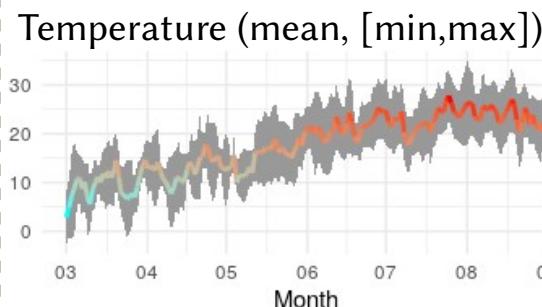
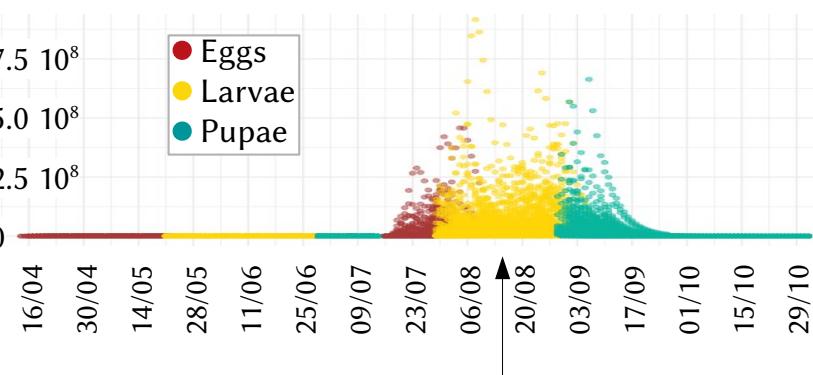
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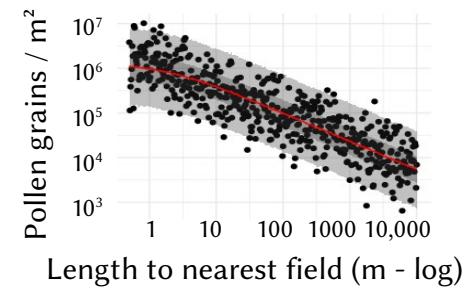
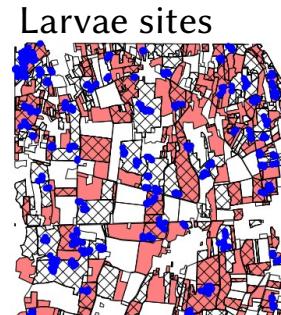


Exposure nbr grains / m²

- Eggs
- Larvae
- Pupae



Exposure profile 15/08



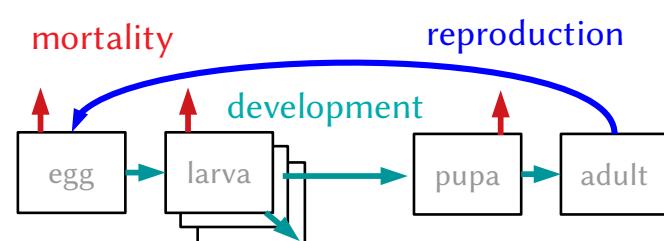
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- ρ, Δ, λ : other parameters to fit

Mechanistic models $\mathcal{M}(\theta)$
parameters θ



6.1 Sublethal on Repro.

$$R(t) = R_0(t) \times \exp(-H_{repro}^+(t))$$

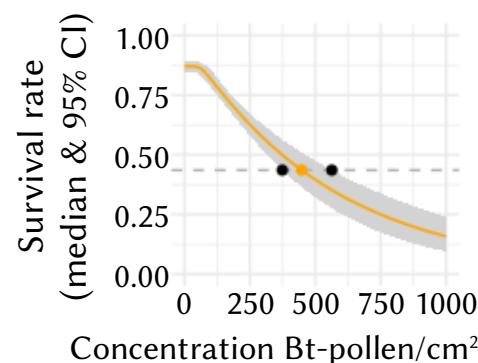
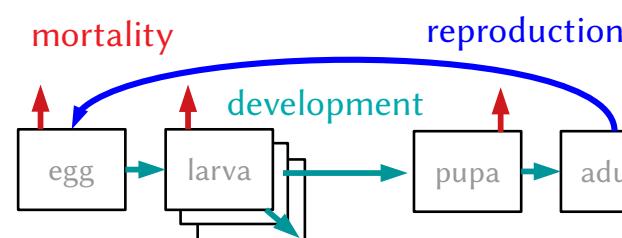
$$N_{G+1}(t) = R(t) \times \text{NID}_G(t)$$

6.2 Sublethal on Growth

$$\delta(t) = \delta_0(t) \times \exp(-H_{dev}^+(t))$$

Mechanistic models $\mathcal{M}(\theta)$
parameters θ

Data $\mathcal{D} = \{\mathcal{E}, \mathcal{O}\}$
experiment \mathcal{E} ; observations \mathcal{O}



6.1 Sublethal on Repro.

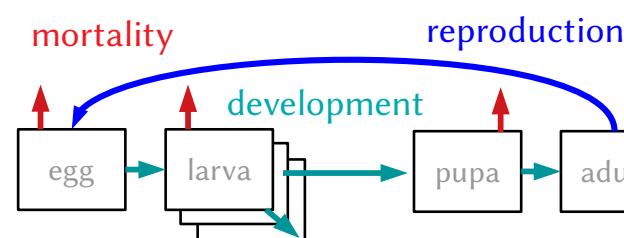
$$R(t) = R_0(t) \times \exp(-H_{repro}^+(t))$$

$$N_{G+1}(t) = R(t) \times \text{NID}_G(t)$$

6.2 Sublethal on Growth

$$\delta(t) = \delta_0(t) \times \exp(-H_{dev}^+(t))$$

Mechanistic models $\mathcal{M}(\theta)$
parameters θ



6.1 Sublethal on Repro.

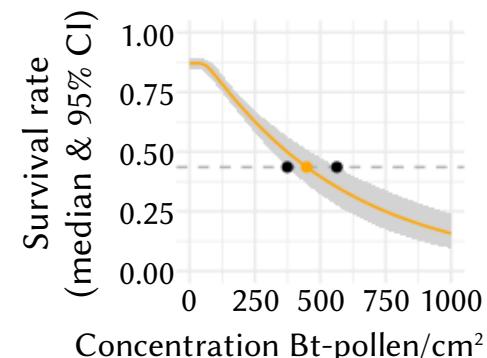
$$R(t) = R_0(t) \times \exp(-H_{repro}^+(t))$$

$$N_{G+1}(t) = R(t) \times \text{NID}_G(t)$$

6.2 Sublethal on Growth

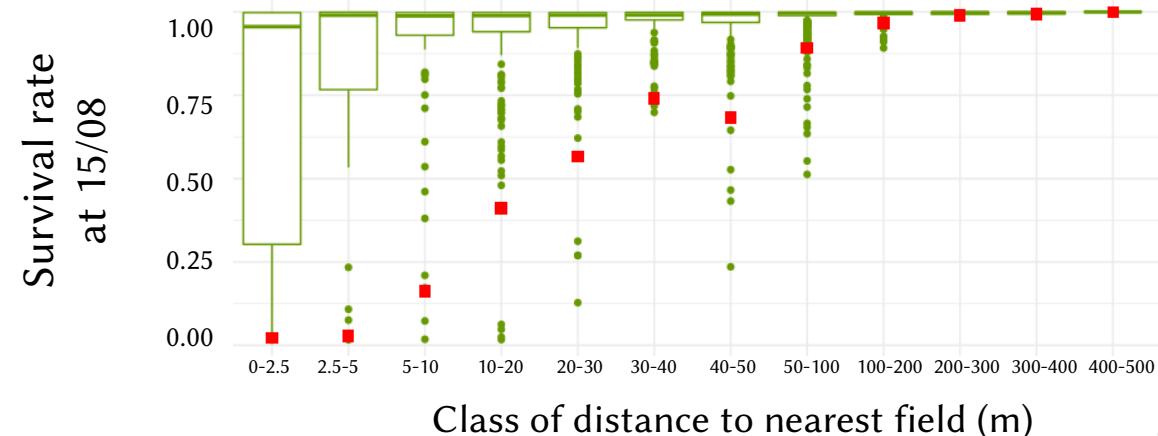
$$\delta(t) = \delta_0(t) \times \exp(-H_{dev}^+(t))$$

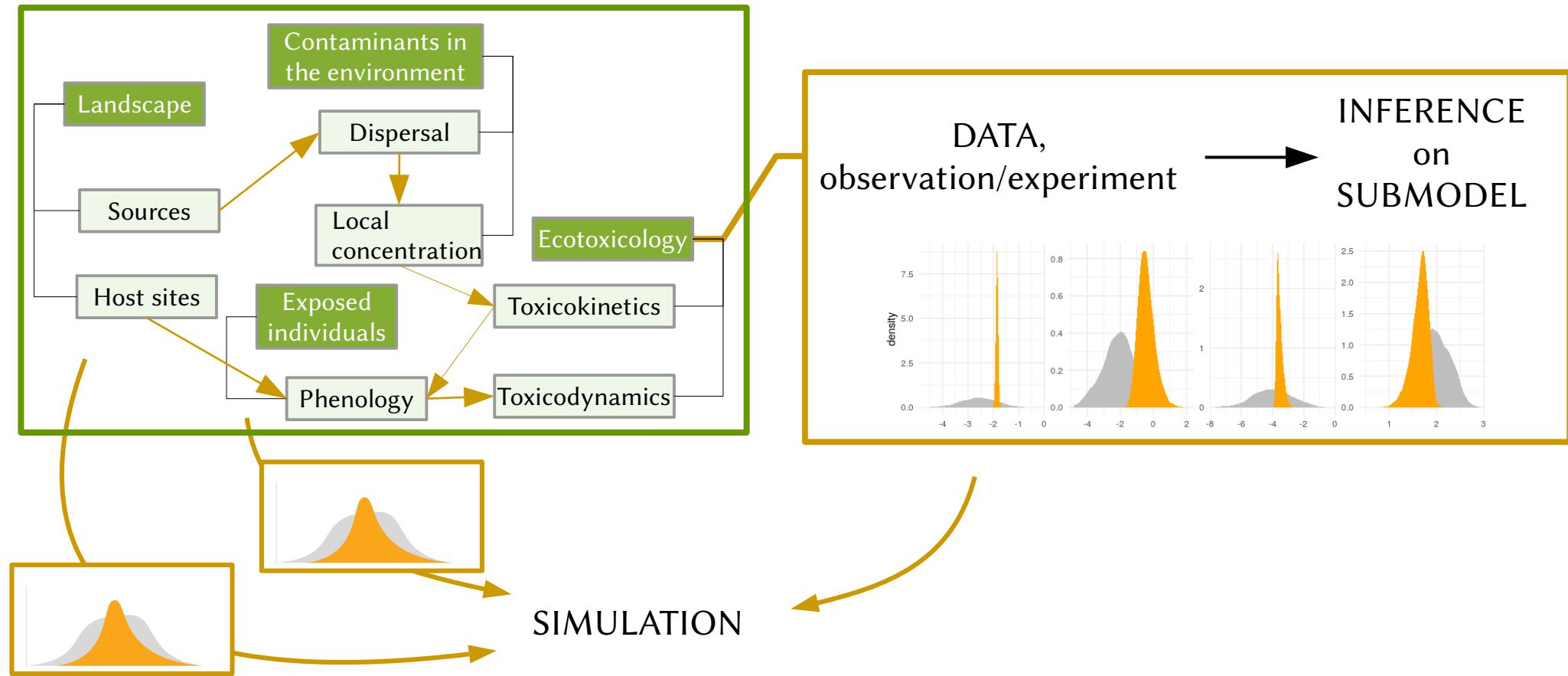
Data $\mathcal{D} = \{\mathcal{E}, \mathcal{O}\}$
experiment \mathcal{E} ; observations \mathcal{O}

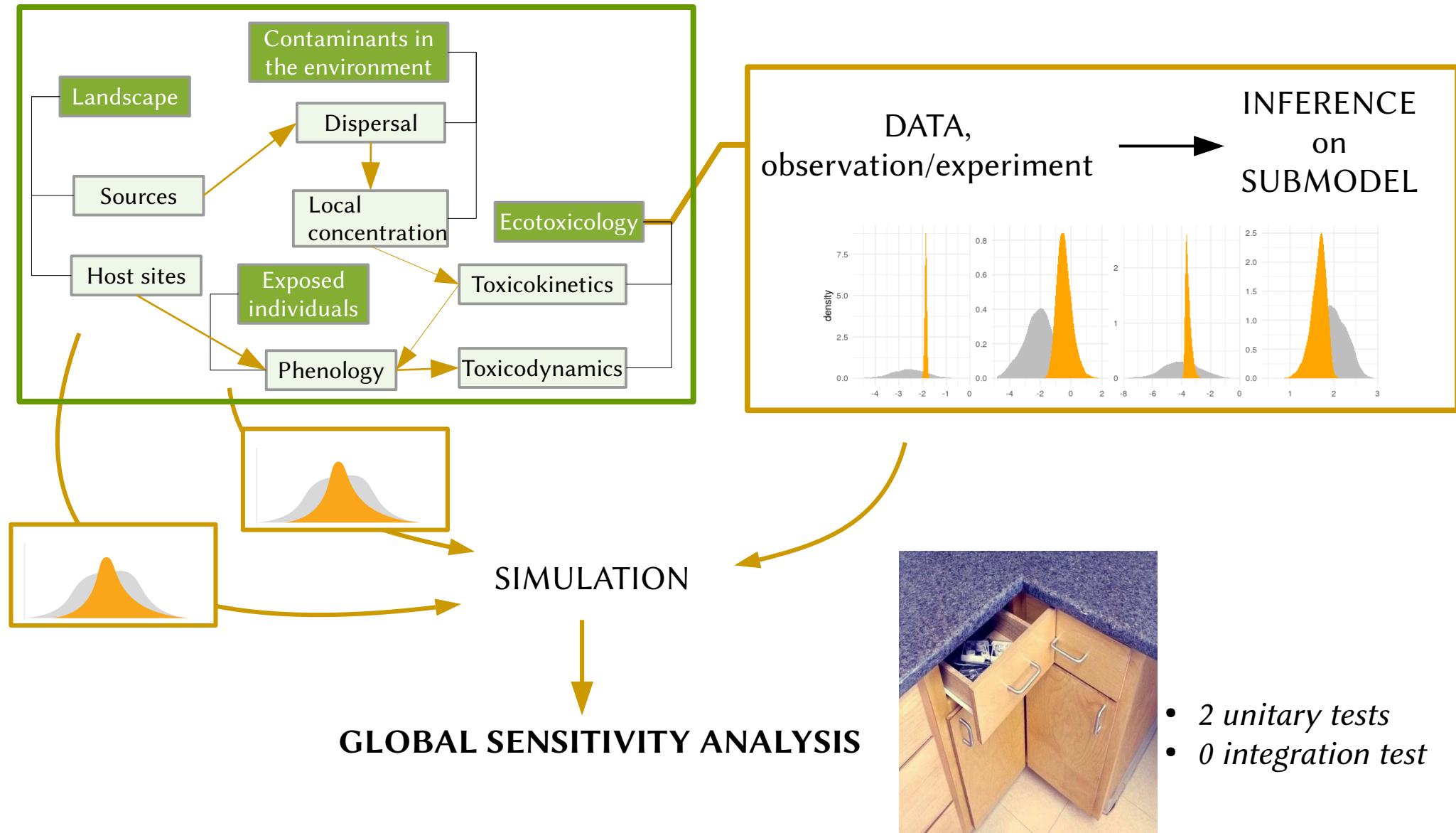


Prediction $\mathcal{R}(\mathcal{E}'|\hat{\theta}(\mathcal{D}))$
environment \mathcal{E}' ; inference params. $\hat{\theta}(\mathcal{D})$

→ In average,
everything is fine...
... risk is in the quantiles

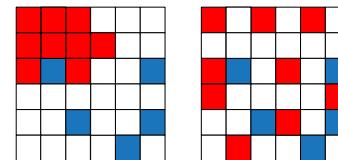




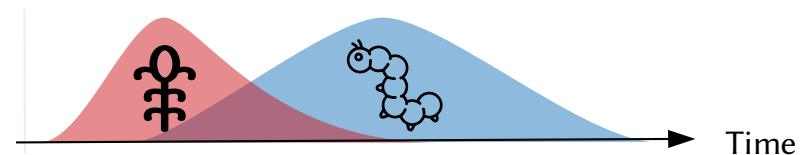


→ 3 driving factors of sensitivity (need further investigation)

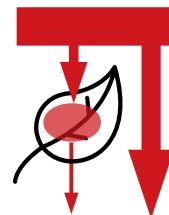
1. Aggregation of GM fields (SPATIAL)



2. Overlapping deposition ↔ sensitive stage

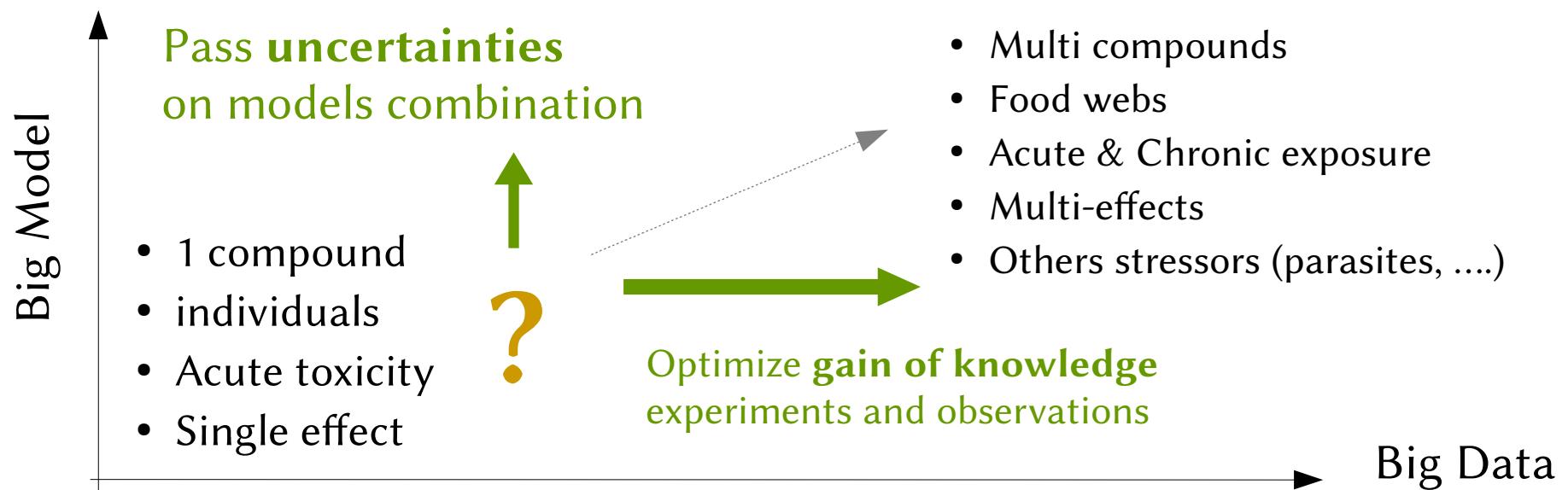


3. Loss and Adherence of pollen



1. Review/Build/Rebuild a set of model of pest-control strategies
→ Open Agent Based Model/Plateform
2. Assessment of their environmental impact
→ Space, Time, Trophic Link, Evolution
3. Uncertainty analysis (Sensitivity, Bayesian inference)
→ lack of knowledge (inputs, output, latent variables)

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Thank you for your attention

$$\mathbb{P}(\text{Thanks}|\text{Attention}) = \frac{\mathbb{P}(\text{Attention}|\text{Thanks}) \times \mathbb{P}(\text{Thanks})}{\mathbb{P}(\text{Attention})}$$

Sciencehood

Goodness of fitting interesting question

